You Only Look Once

CSCI 4907 Guest Lecture

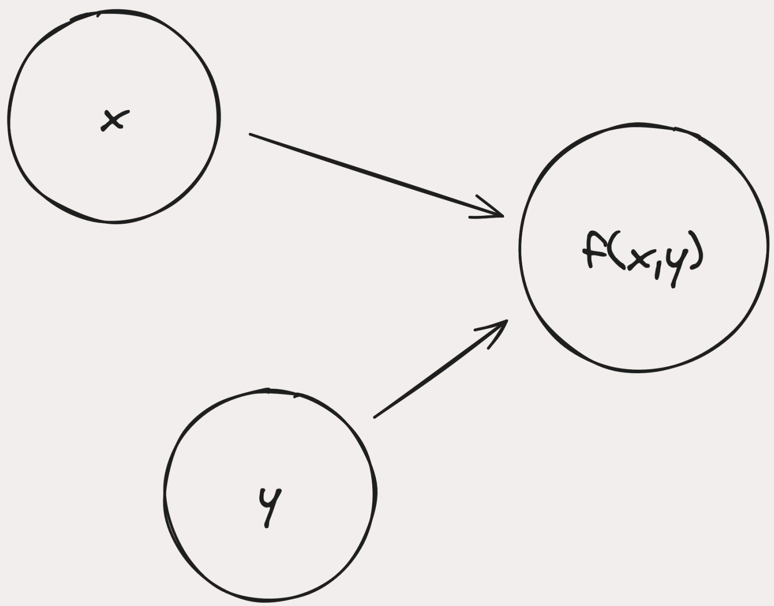
Joe Goldfrank

There Is No Way I Can Possibly Speenrun All Of Neural Networks In One Hour

Computational Graphs

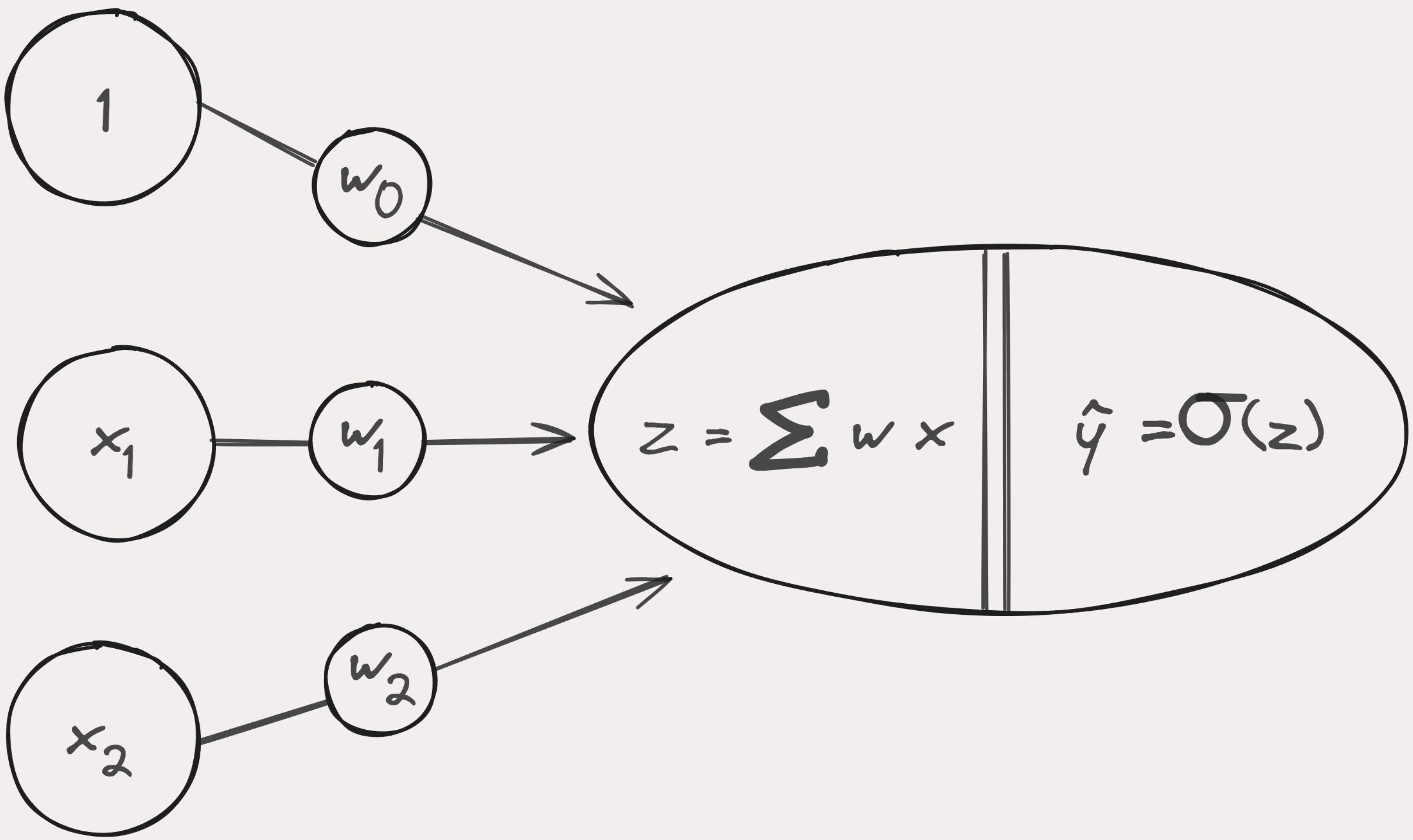
- Representation of mathematical operations using *directed acyclic* graphs
  - Used by neural networks for computation

Nodes can be variables or functions



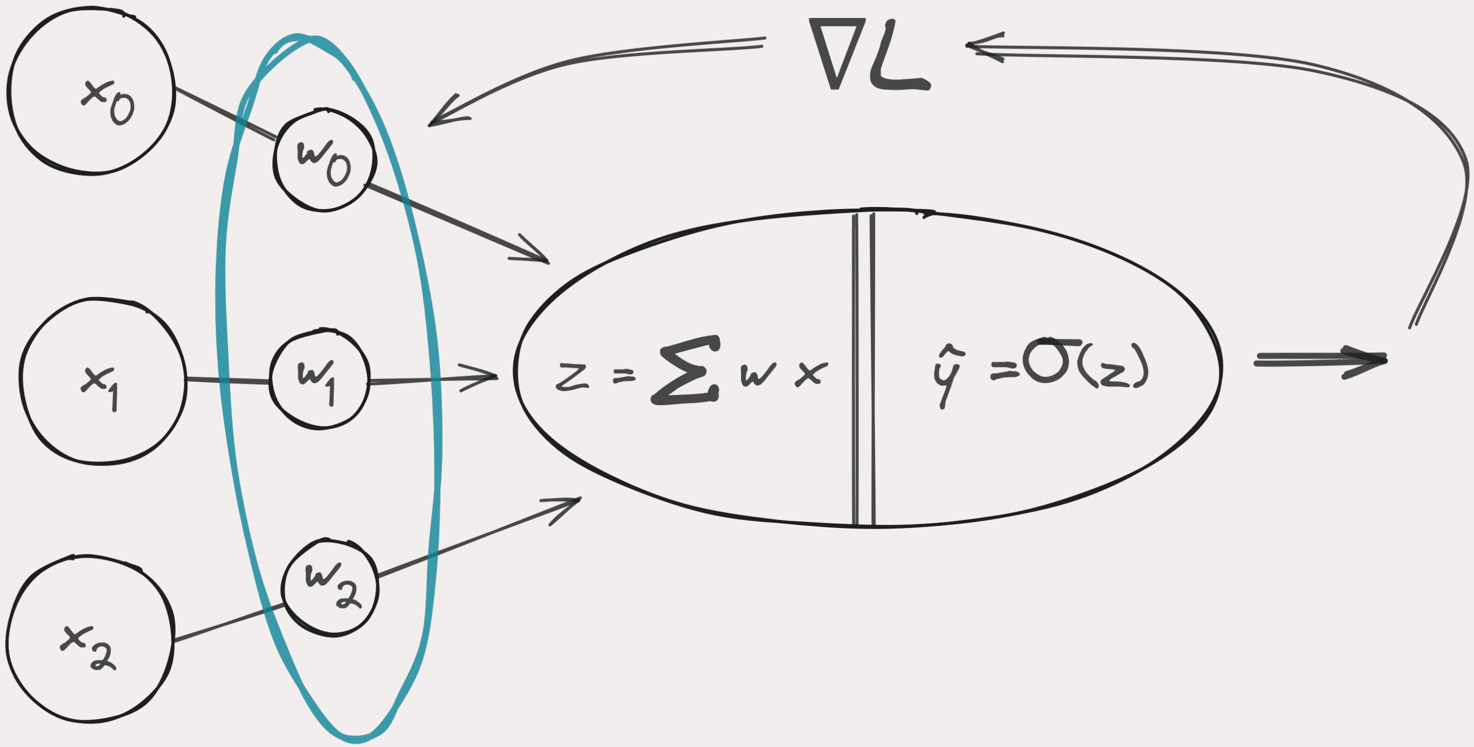
Activation Function

- Separate *data*, *weights*, and *structure*



Updating the Graph

$$\vec{w} = \vec{w} - LR \cdot \nabla L$$



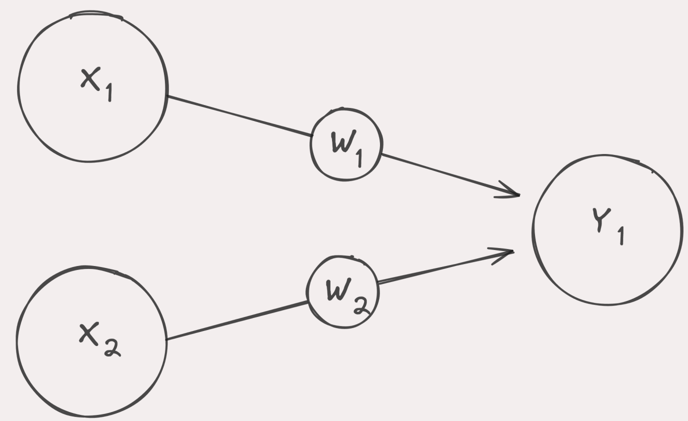
Neuron Computation

- Can also represent as vectors

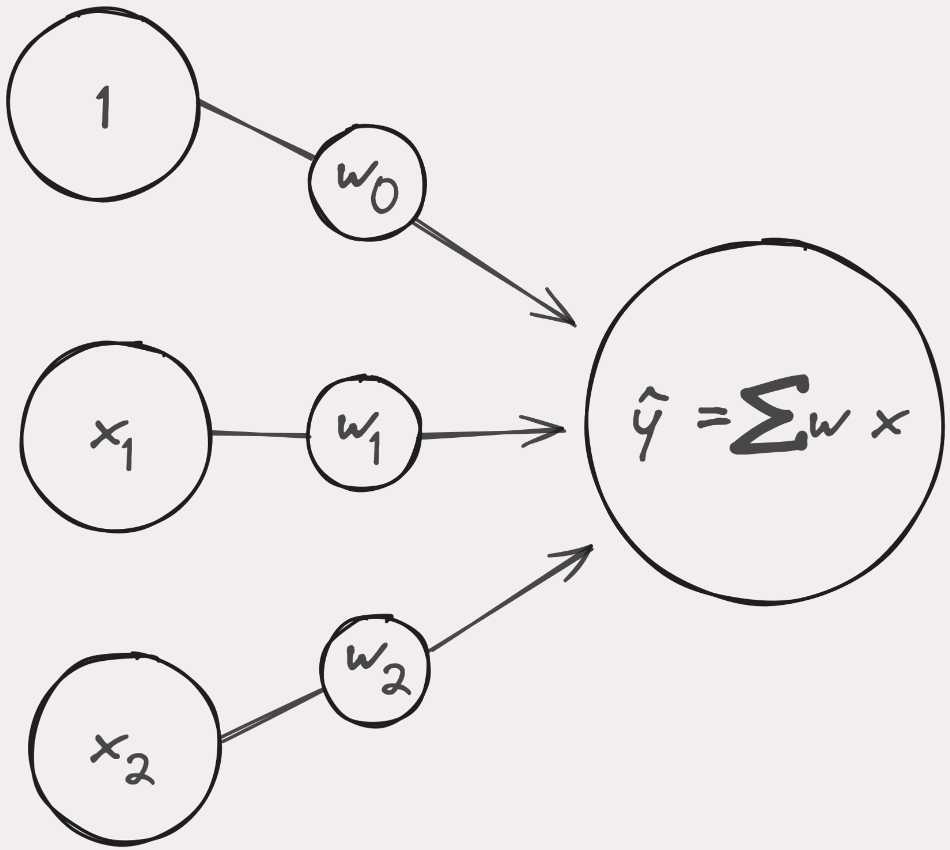
$$\sum x \times w = y$$

$$\begin{bmatrix} x_1 & x_2 \end{bmatrix} \cdot \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = y$$

$$\vec{x} \cdot \vec{w} = y$$

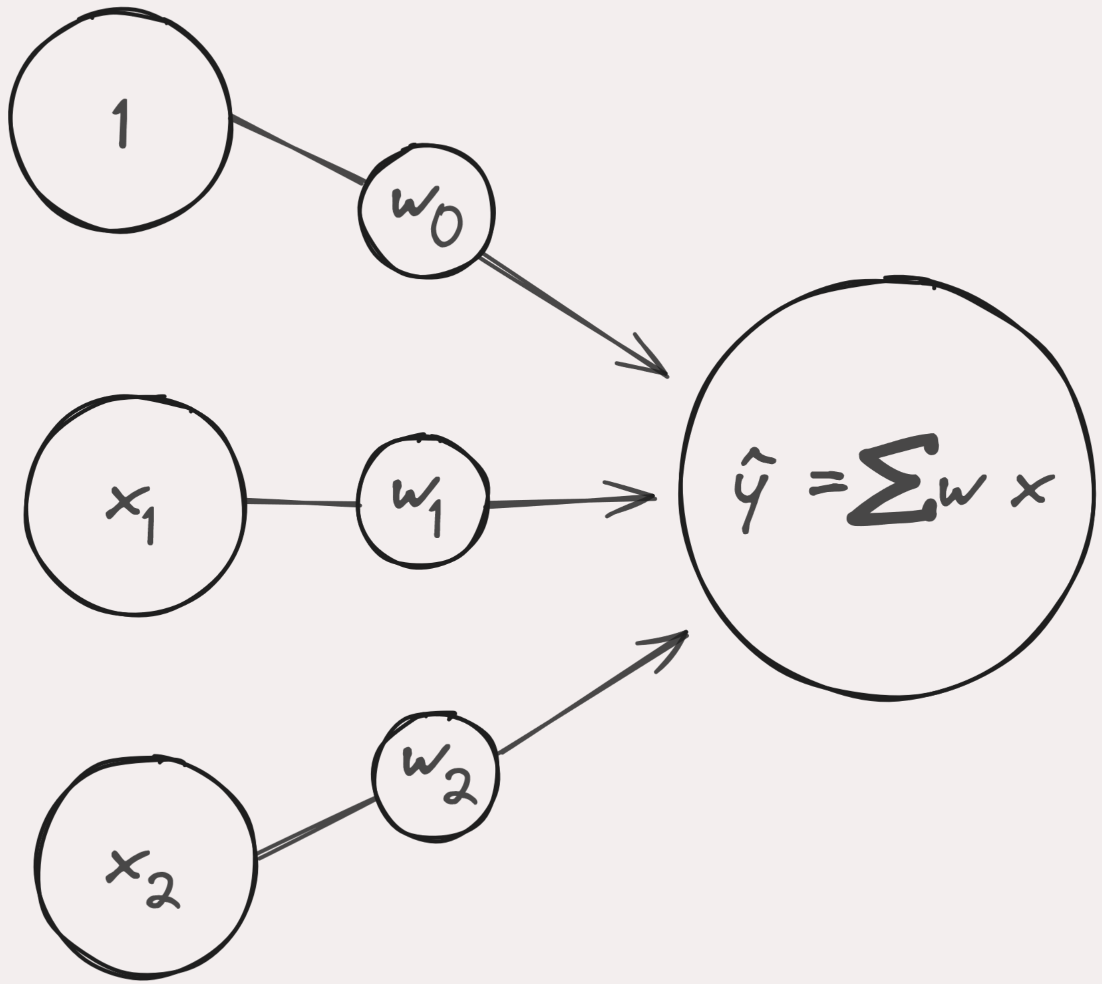


Linear Regression Computational Graph

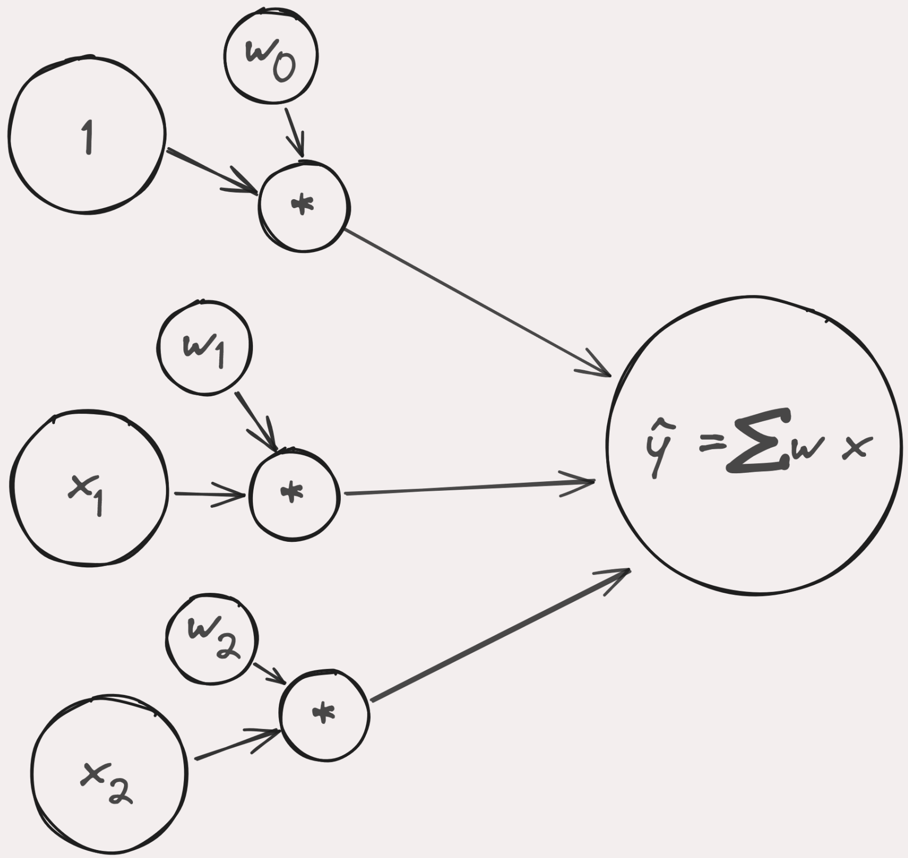


Backpropagation

Linear Regression

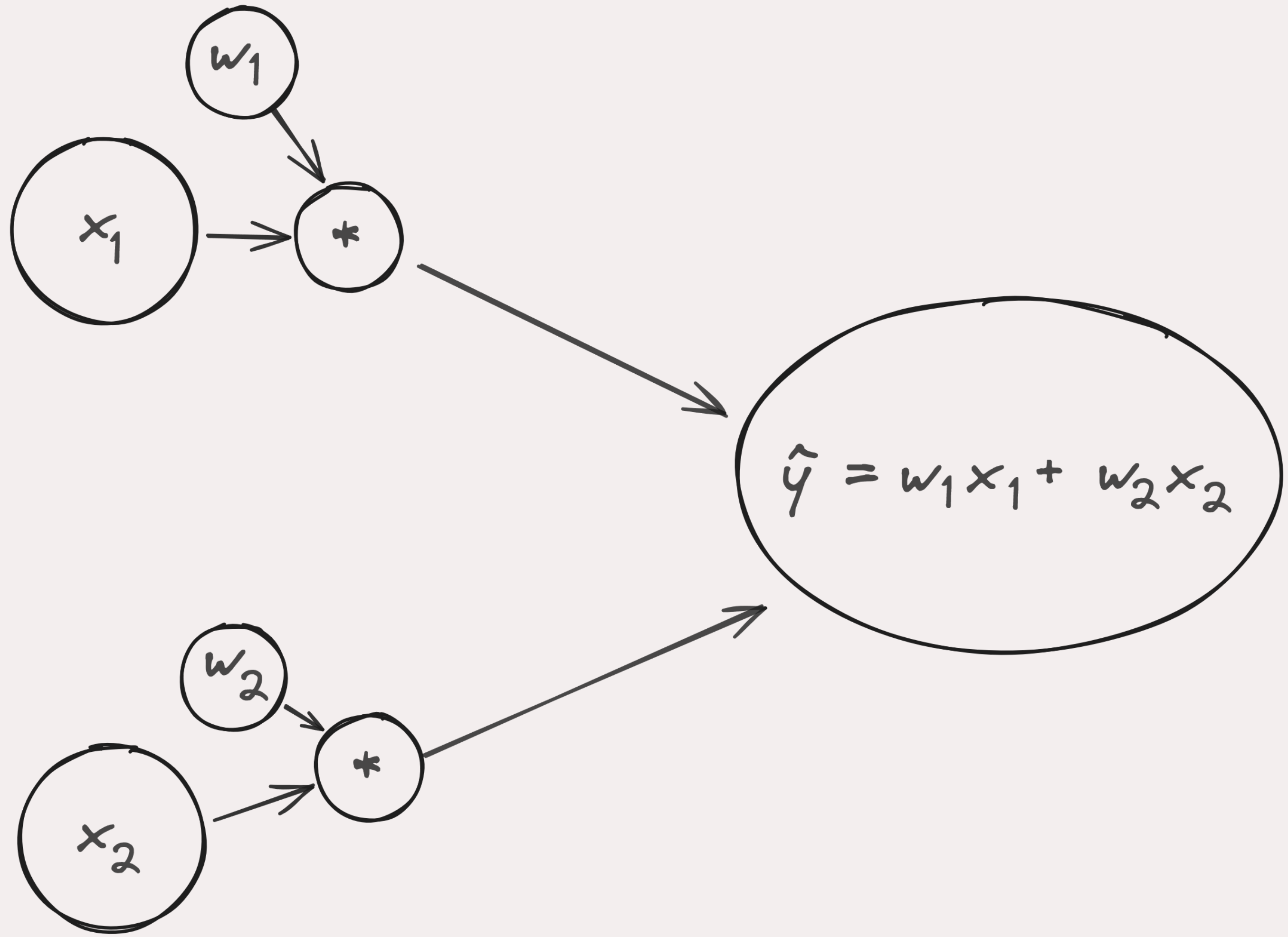


Multiplication - Explicit



Why?

“Simplified”

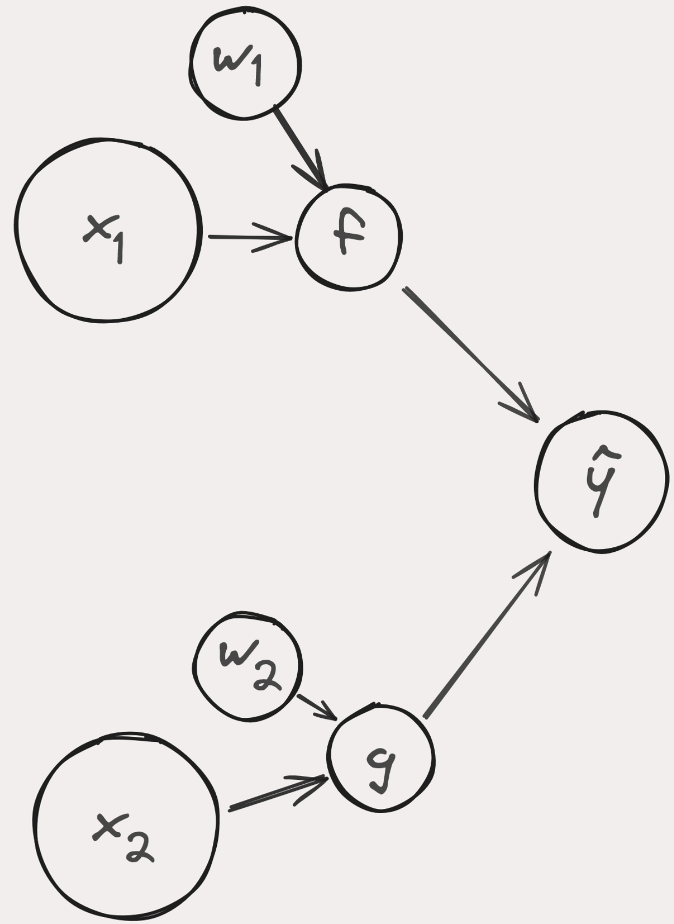


Functions

$$f(a,b) = a \cdot b$$
$$g(a,b) = a \cdot b$$
$$\hat{y}(a,b) = a + b$$

Shown:

$$f(w_1, x_1)$$
$$g(w_2, x_2)$$
$$\hat{y}(f, g)$$



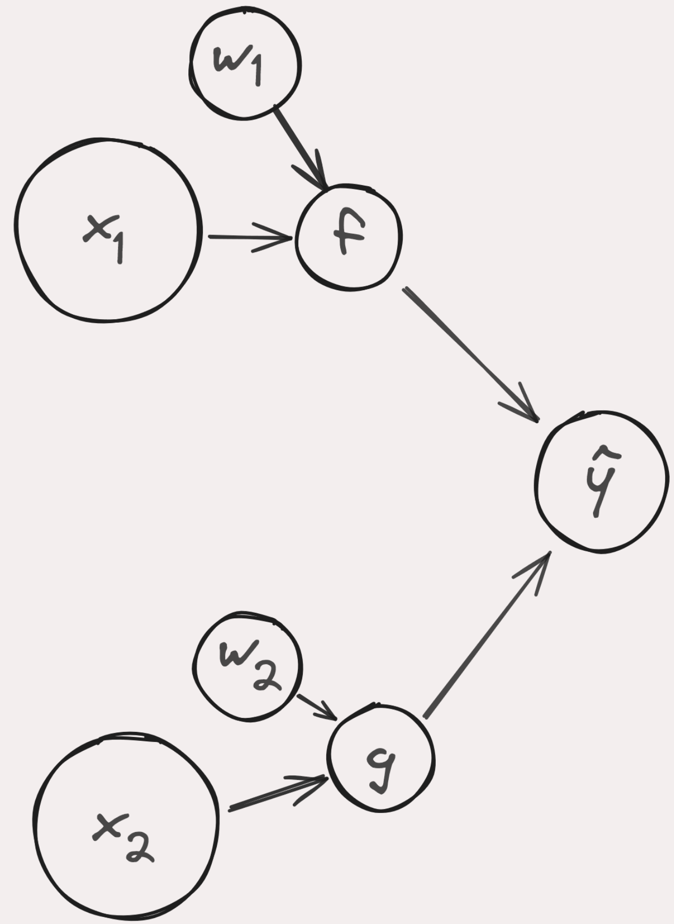
Derivatives

$$f(a,b) = a \cdot b$$
$$g(a,b) = a \cdot b$$
$$\hat{y}(a,b) = a + b$$

$$\frac{\partial f}{\partial a} = b \; \frac{\partial f}{\partial b} = a$$

$$\frac{\partial g}{\partial a} = b \; \frac{\partial g}{\partial b} = a$$

$$\frac{\partial \hat{y}}{\partial a} = 1 \; \frac{\partial \hat{y}}{\partial b} = 1$$



Forward

$$f(a,b) = a \cdot b$$
$$g(a,b) = a \cdot b$$
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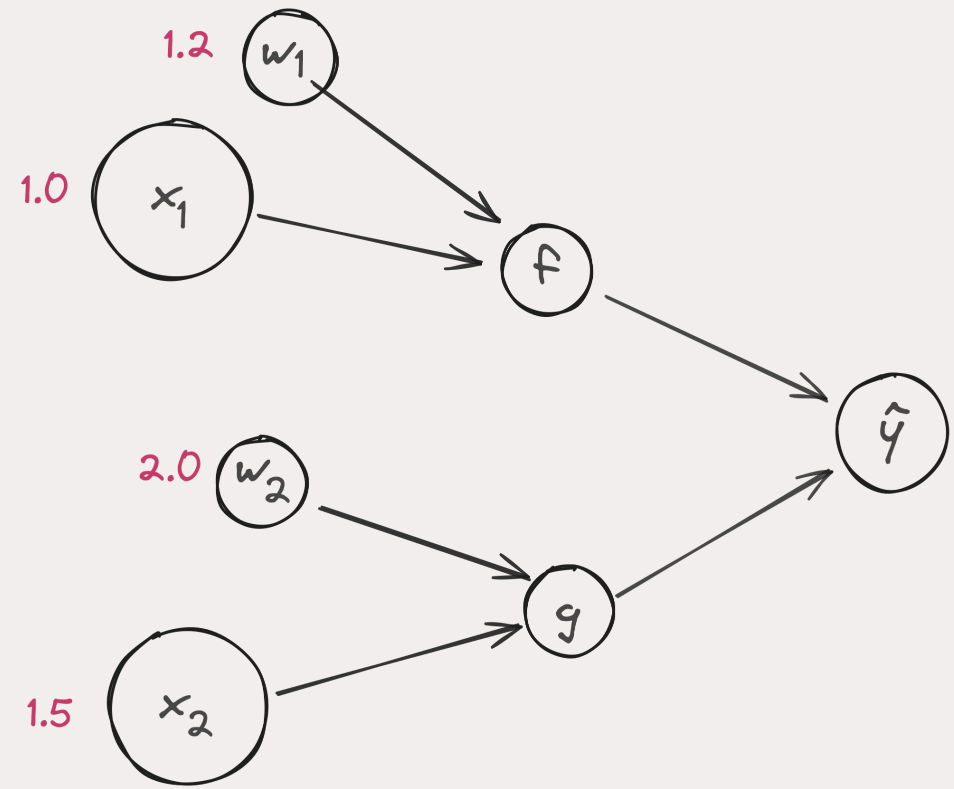

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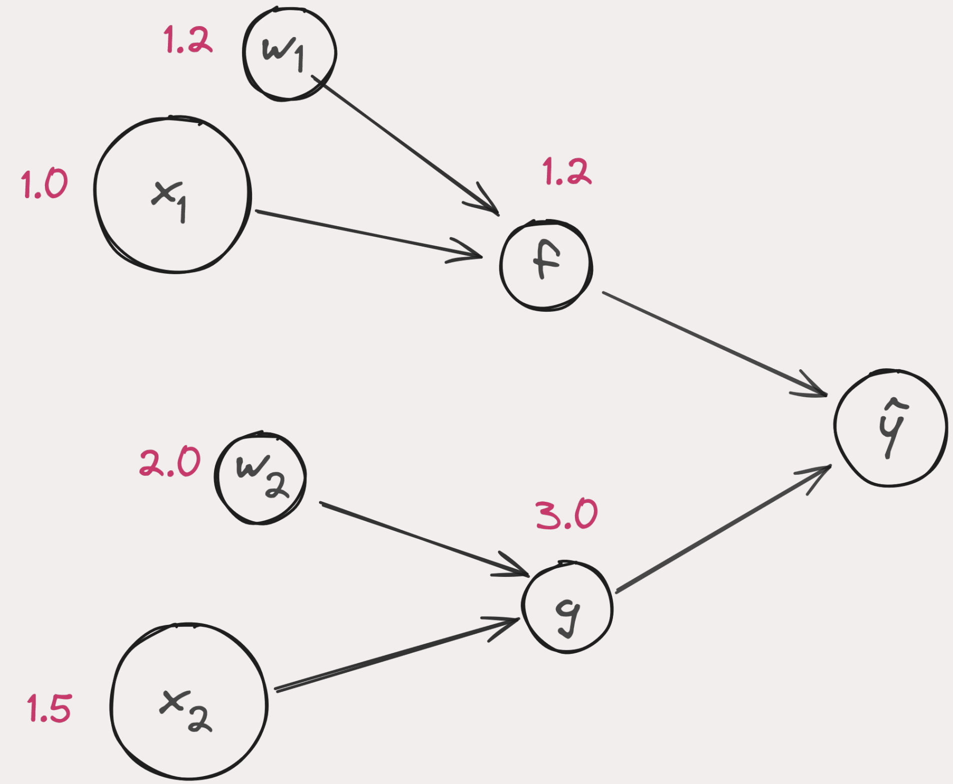

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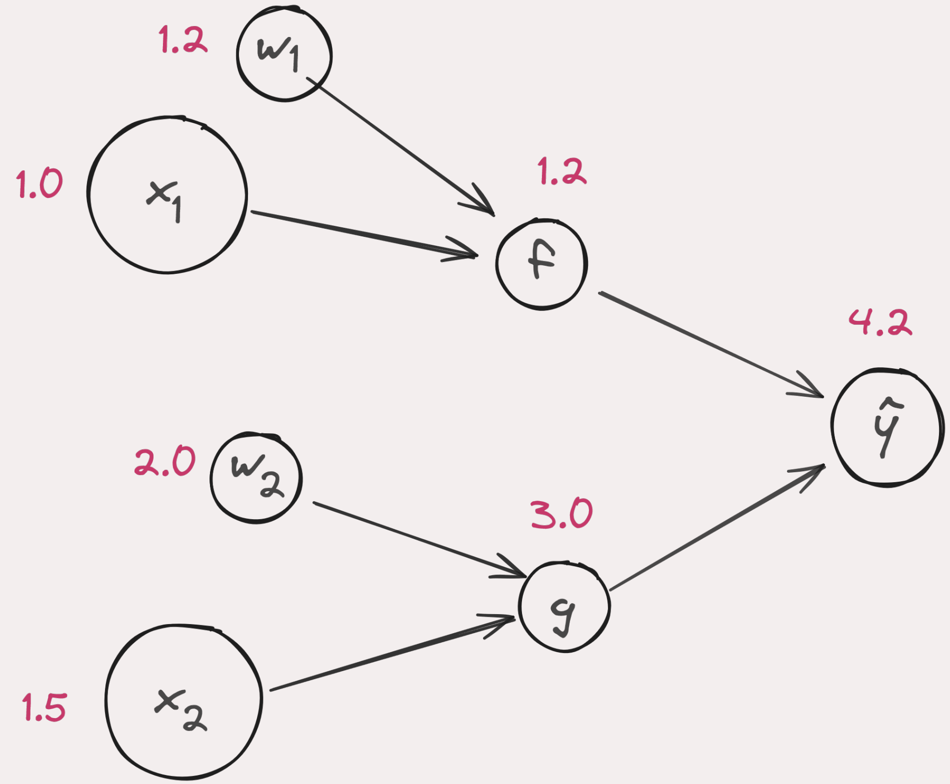

Backward!

- We're interested in $\frac{\partial \hat{y}}{\partial w_i}$
  - Update weights
  - Train model
- Use chain rule:

$$f(x) = f(g(x))$$

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial g}\frac{\partial g}{\partial x}$$

Backward

$$f(a,b) = a \cdot b$$
$$g(a,b) = a \cdot b$$
$$\hat{y}(a,b) = a + b$$

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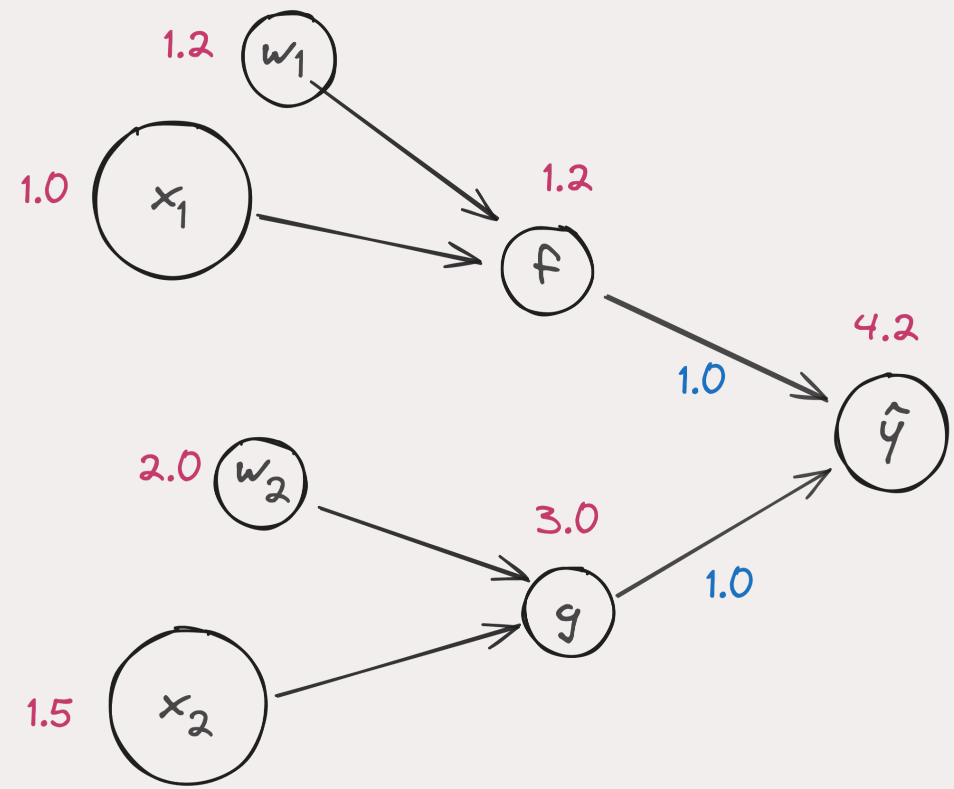

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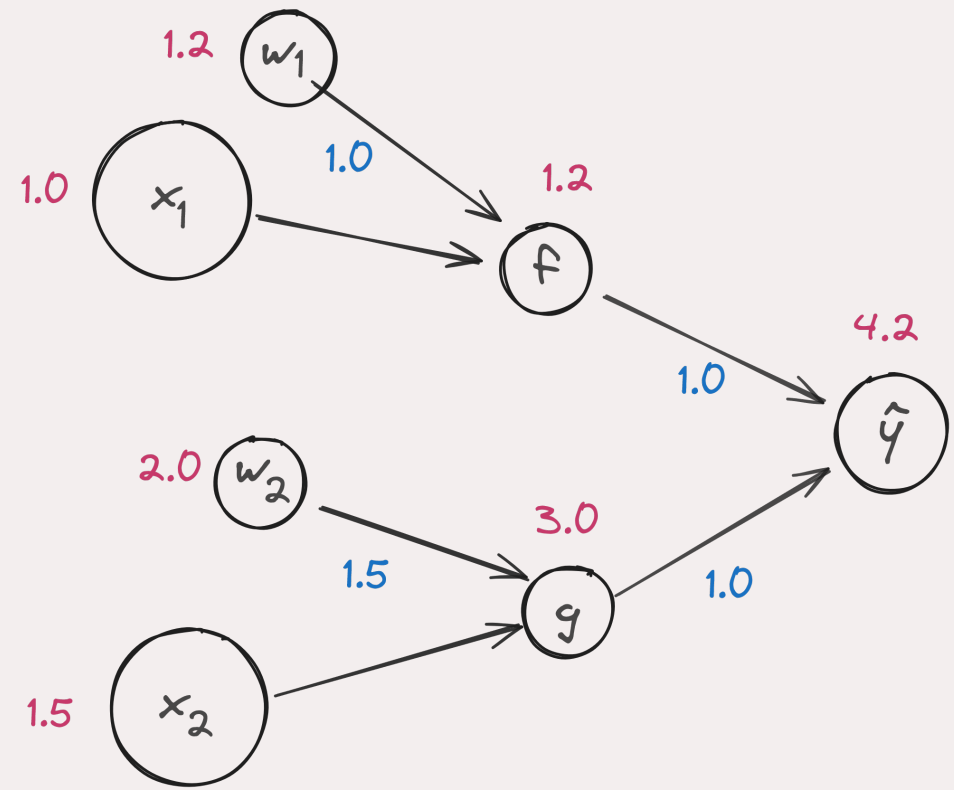


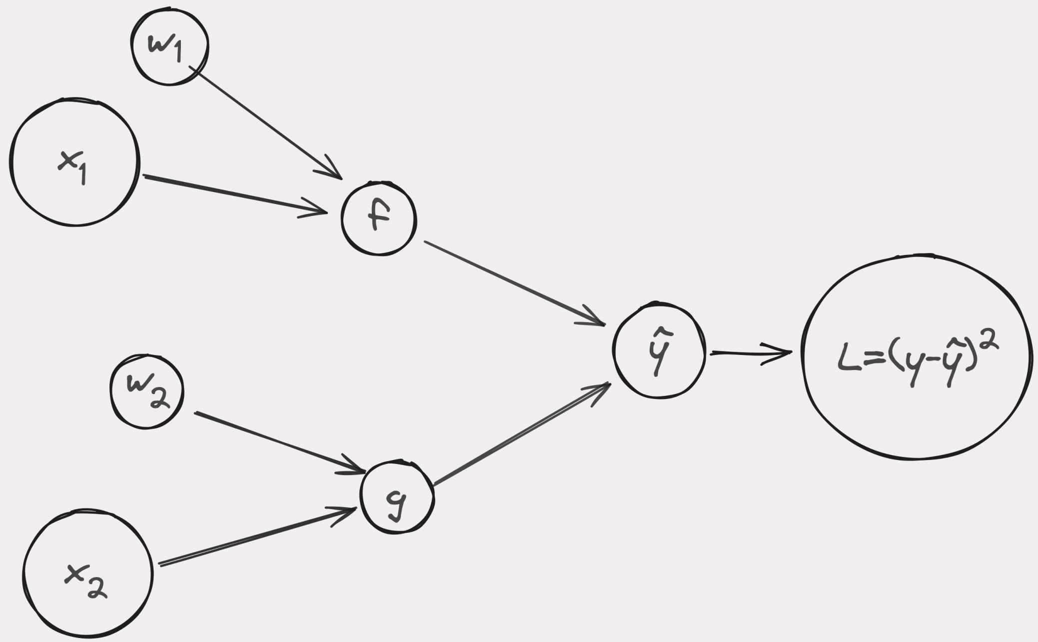
Is This Loss?

$$\frac{\partial f}{\partial a} = b \ \frac{\partial f}{\partial b} = a$$

$$\frac{\partial g}{\partial a} = b \ \frac{\partial g}{\partial b} = a$$

$$\frac{\partial \hat{y}}{\partial a} = 1 \ \frac{\partial \hat{y}}{\partial b} = 1$$

$$\frac{\partial L}{\partial \hat{y}} = -2(y - \hat{y})$$



Loss Decomposed

$$h = y - \hat{y}$$
$$L = h^2$$

$$\frac{\partial f}{\partial a} = b \; \frac{\partial f}{\partial b} = a$$

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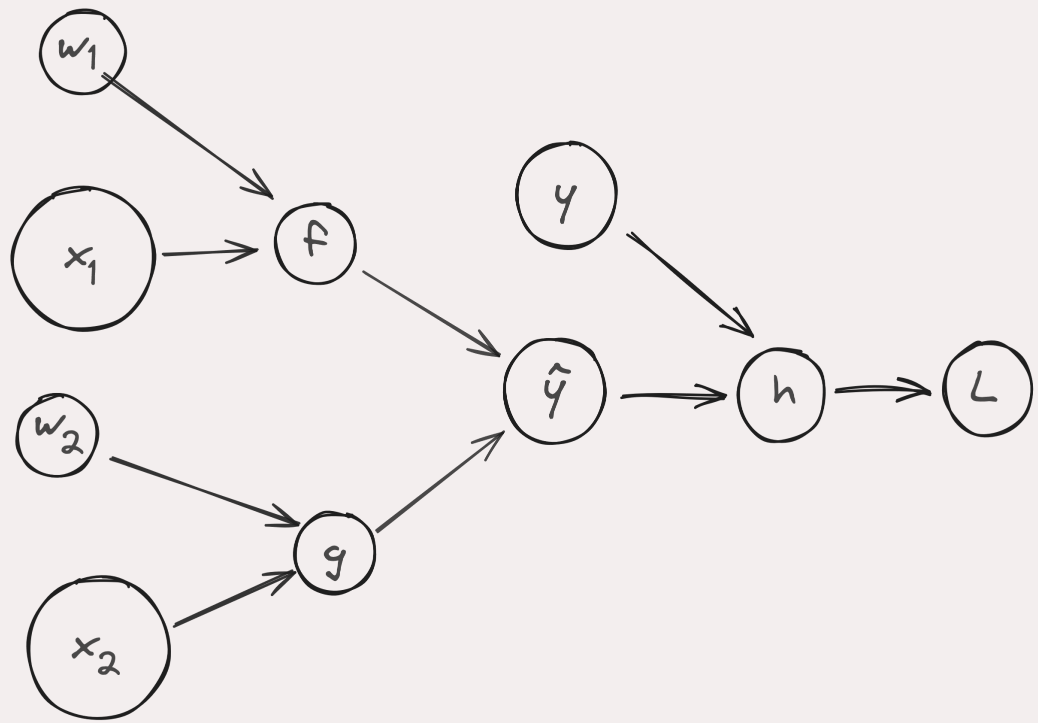

Loss Decomposed

$$\frac{\partial h}{\partial \hat{y}} = -1$$

$$\frac{\partial L}{\partial h} = 2 \cdot h$$

$$\frac{\partial f}{\partial a} = b \ \frac{\partial f}{\partial b} = a$$

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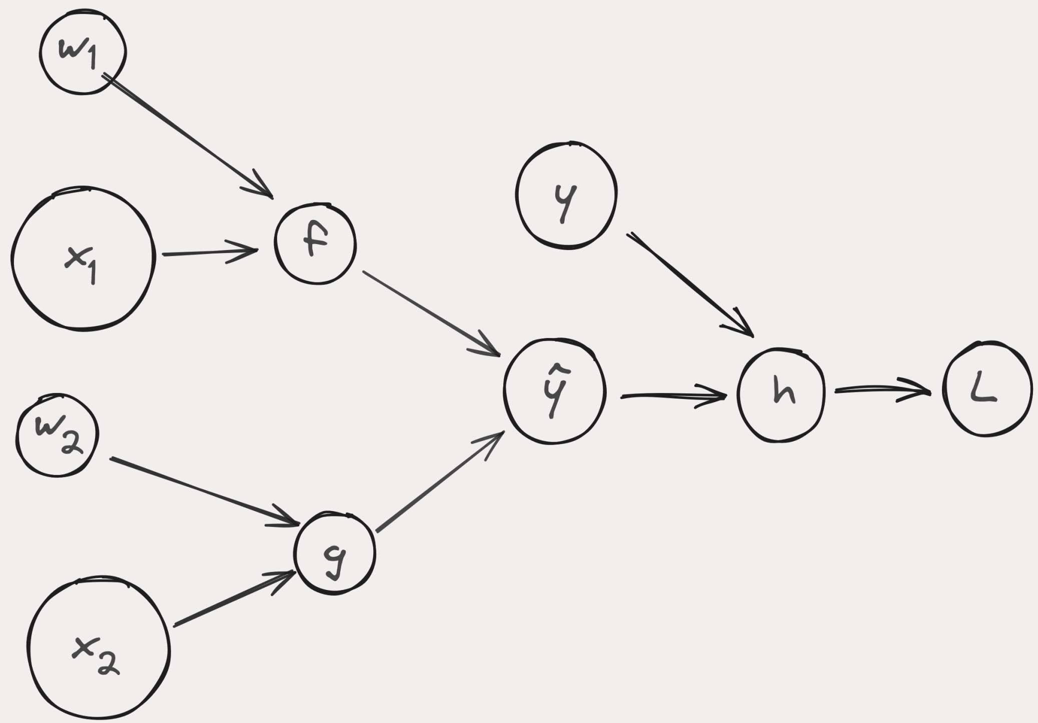

Forward

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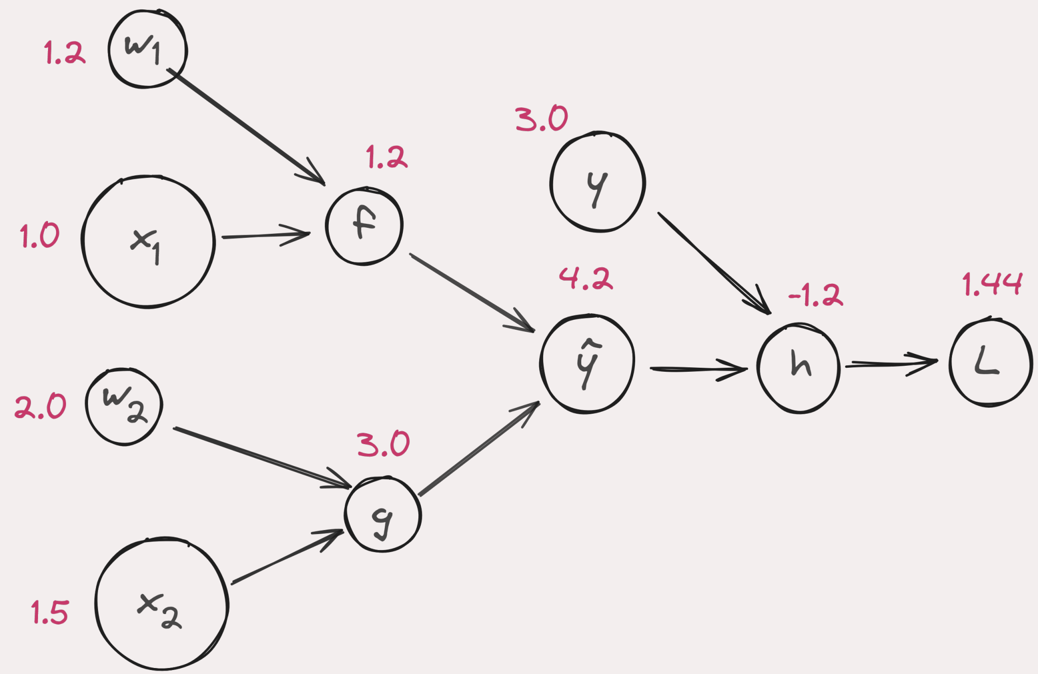

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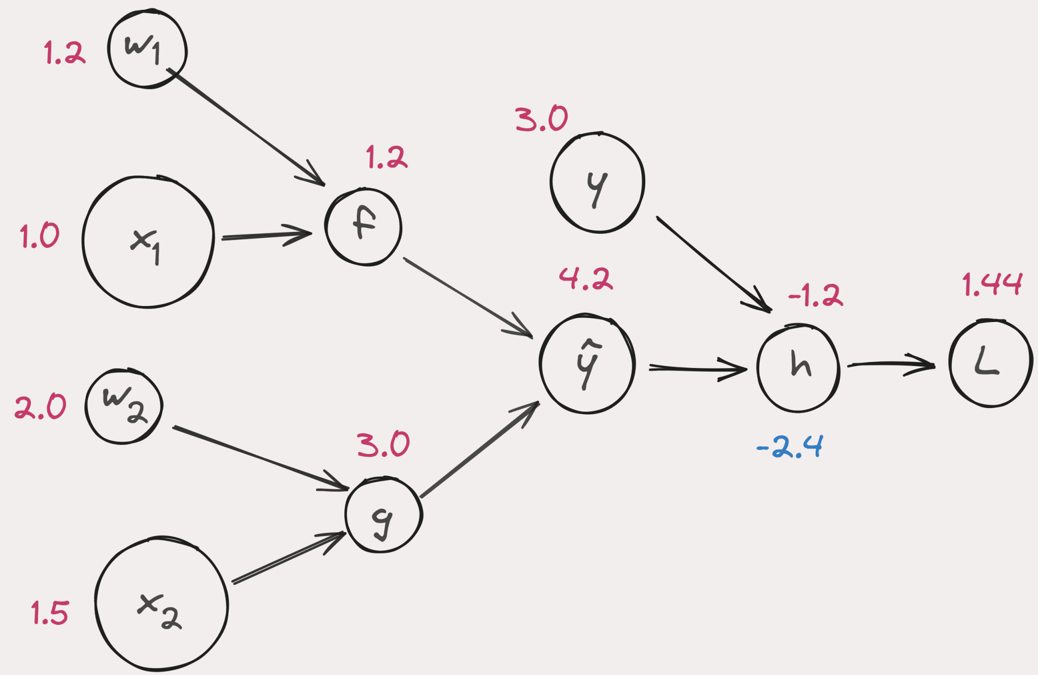

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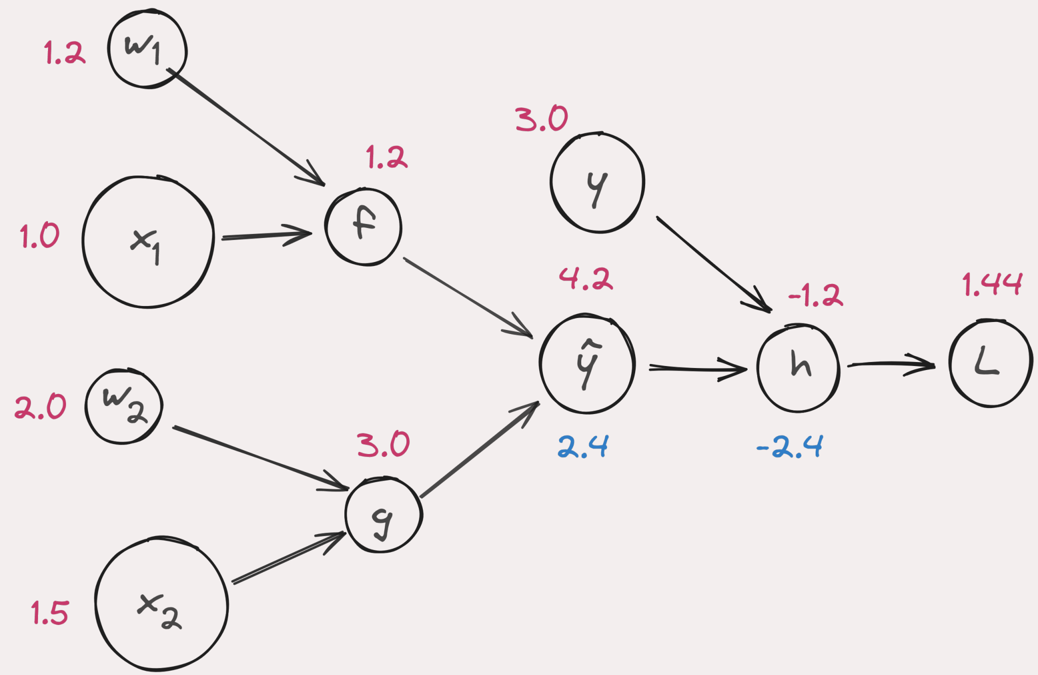

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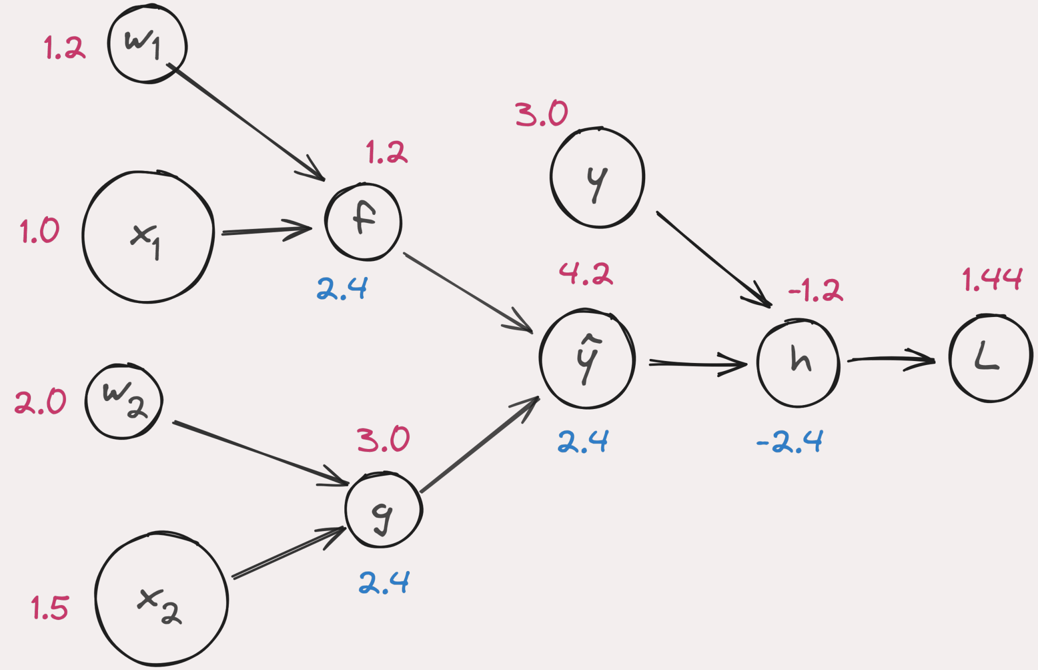

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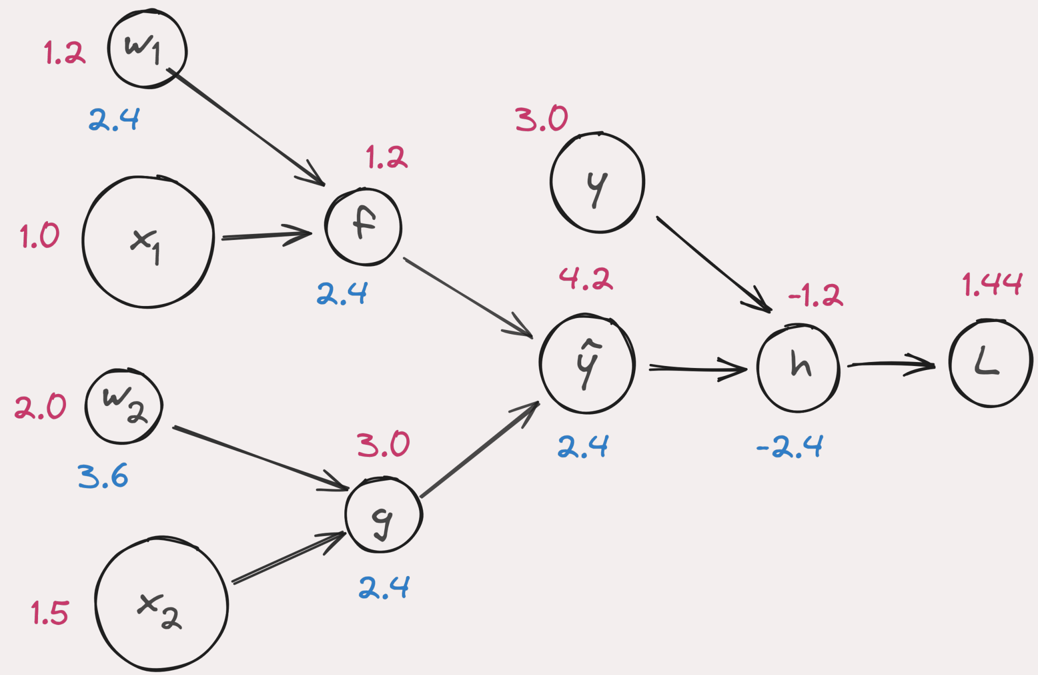
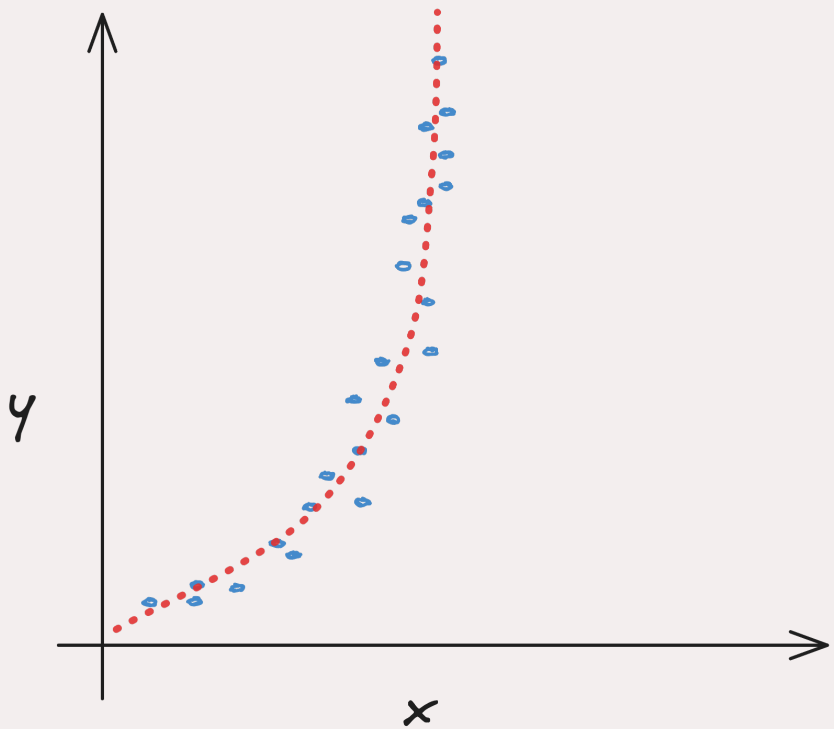
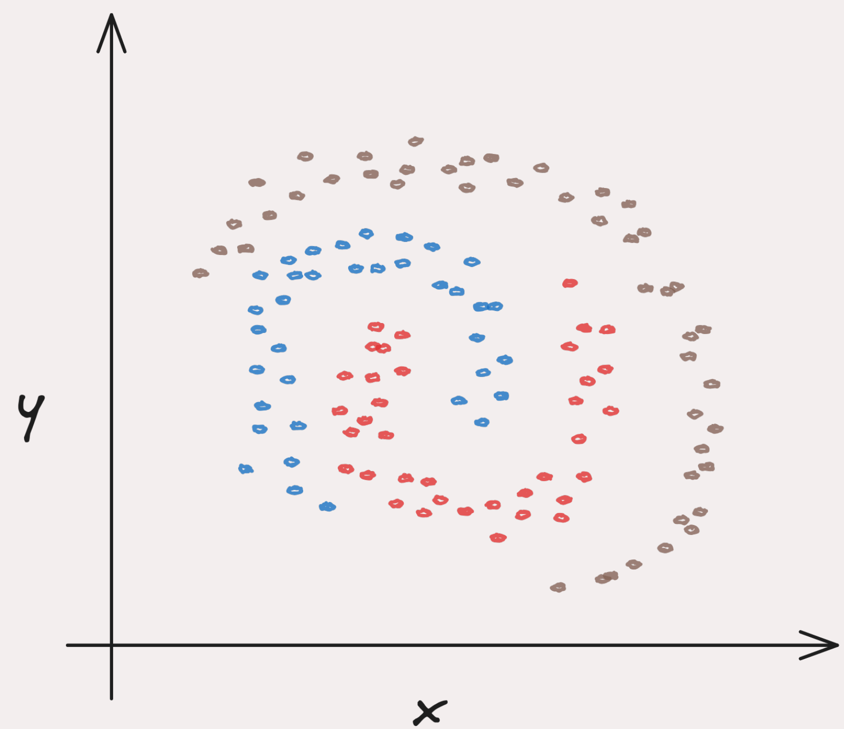


Nonlinearities

- Linear activation function does a poor job approximating non-linear relationships



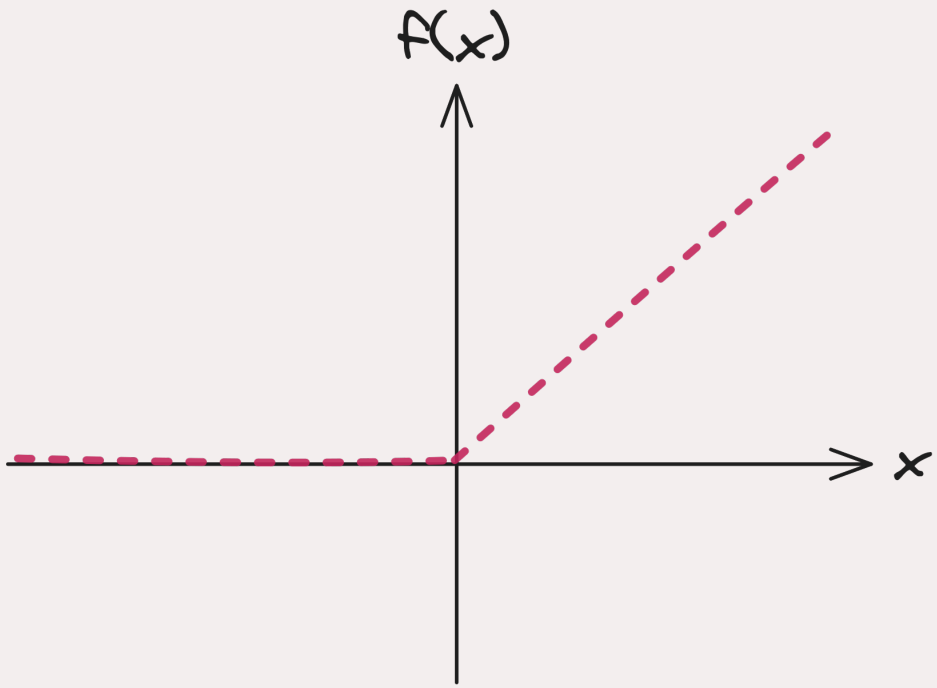


Introducing the ReLU

Rectified Linear Unit

$$f(x) = \begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases}$$

Derivative?



ReLU Derivative

$$\frac{\partial}{\partial x}\begin{cases} x & x > 0 \\ 0 & x \leq 0 \end{cases}$$

$$= \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases}$$

😌

Softmax

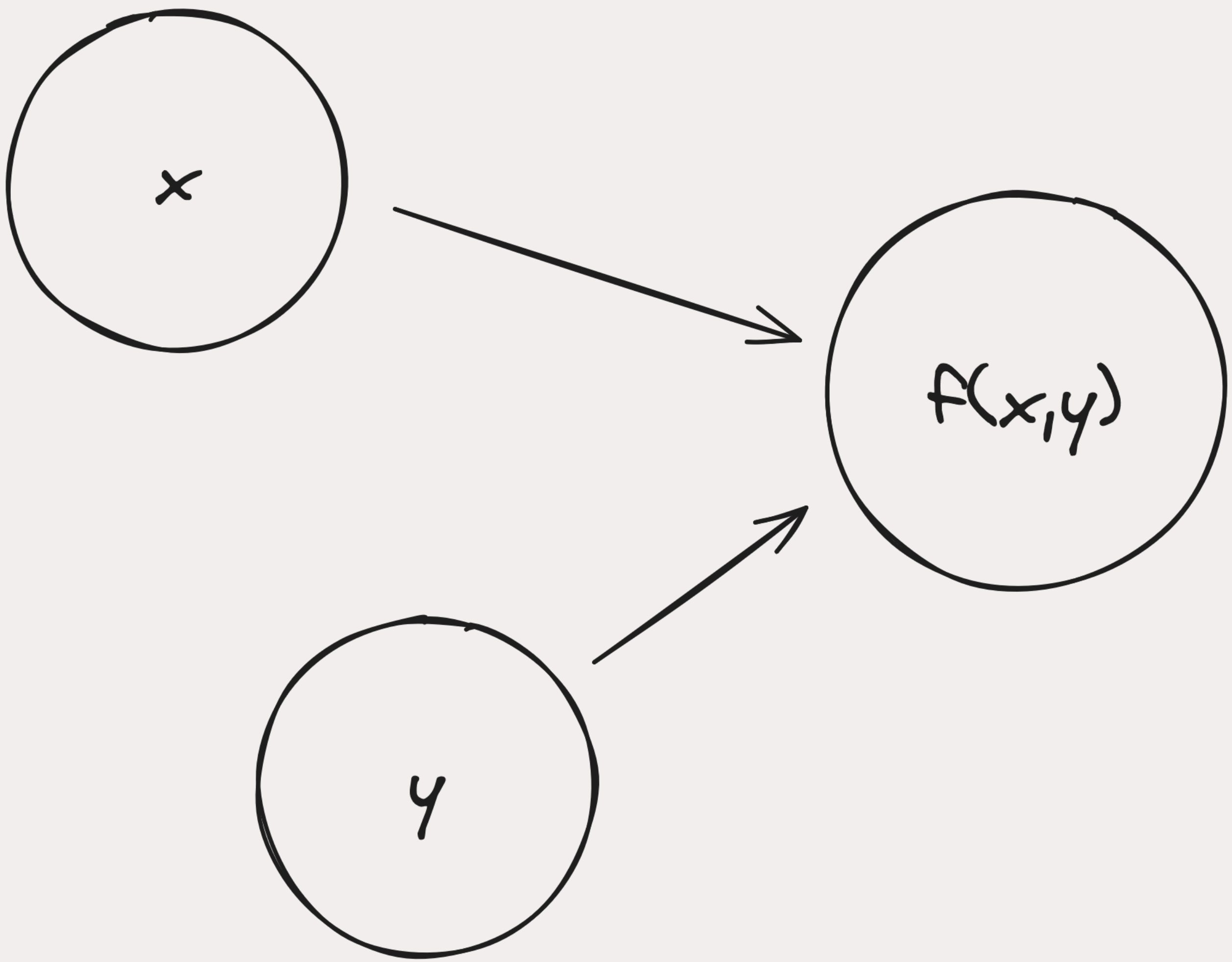
- Used for multi-class classification problems
- Weighted probability of data representing class j
    - Given total set of classes K

$$p(y = j|x) = \frac{e^{x \cdot w_j}}{\sum_K e^{x \cdot w_k}}$$

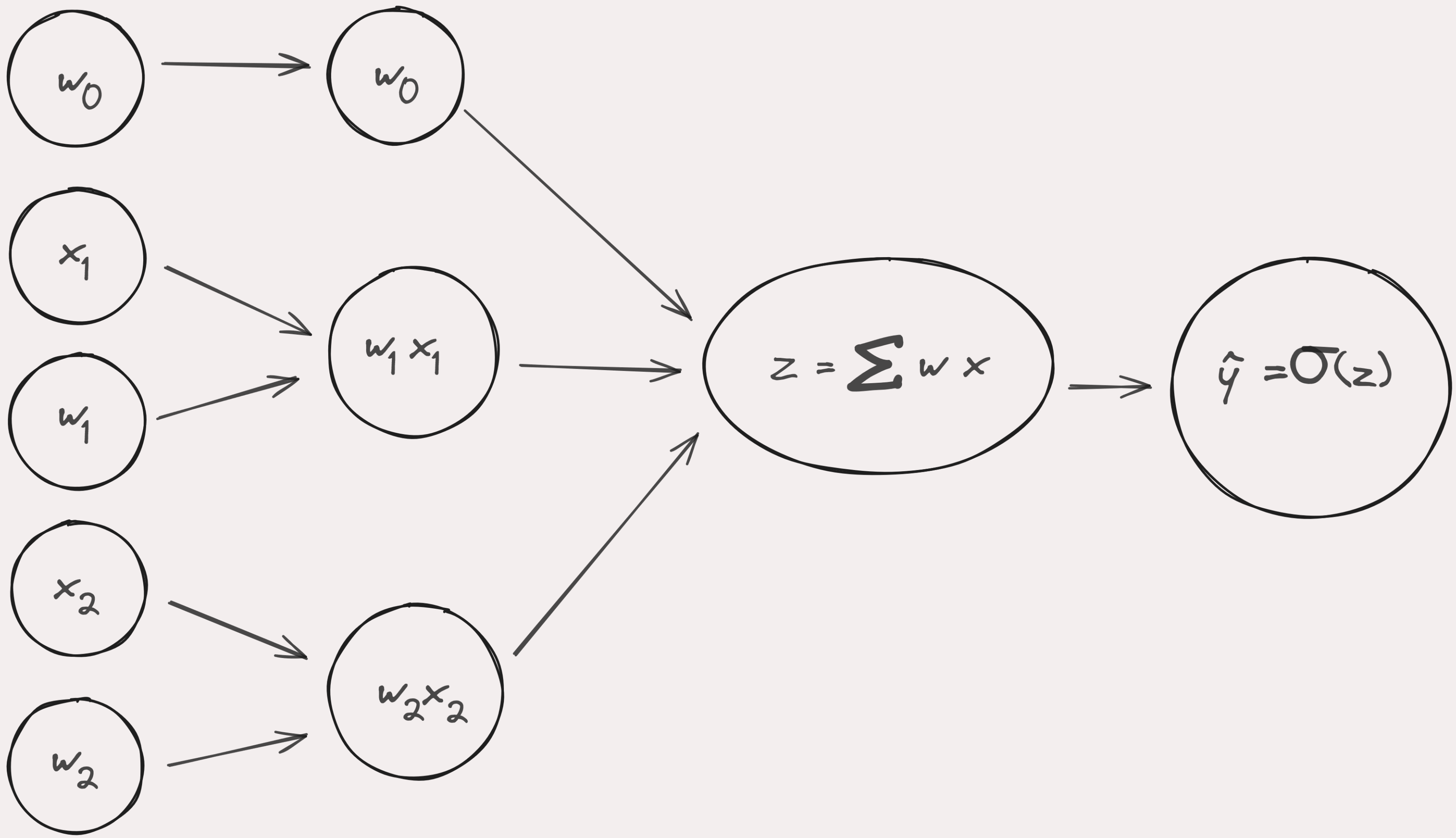
- Typically used in output layers

Something About Only Looking Once

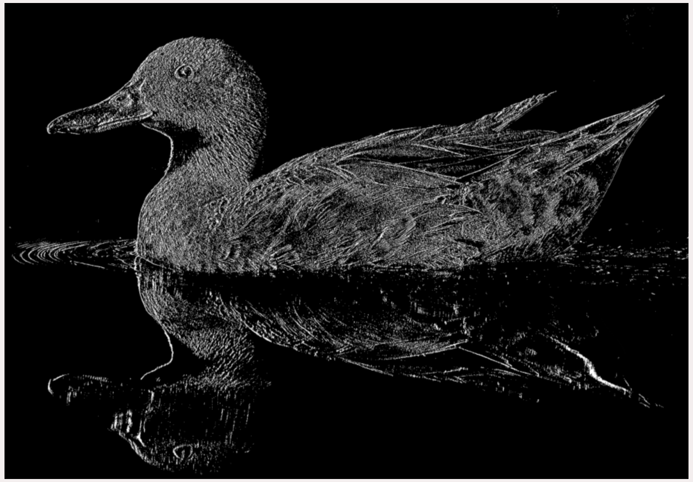
How It Started



How It Started



How It’s Going



```
edge_kernel = k*np.array([[0, 0, 0, 0, 0],
                          [0, 0, 0, 0, 0],
                          [0, -1, 1, 0, 0],
                          [0, 0, 0, 0, 0],
                          [0, 0, 0, 0, 0]])
```

```
def deep_model(optimizer='adam', init='normal'):
    model = Sequential()
    model.add(Dense(120, input_dim=60, kernel_initializer=init))
    model.add(BatchNormalization(momentum=0.5, epsilon=0.001))
    model.add(Activation('relu'))
    model.add(Dense(60, kernel_initializer=init))
    model.add(BatchNormalization(momentum=0.5, epsilon=0.001))
    model.add(Activation('relu'))
    model.add(Dense(60, kernel_initializer=init))
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    model.add(Activation('relu'))
    model.add(Dense(60, kernel_initializer=init))
    model.add(BatchNormalization(momentum=0.5, epsilon=0.001))
    model.add(Activation('relu'))
    model.add(Dense(1, kernel_initializer=init, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer=optimizer, metrics=['accuracy'])
    return model
```
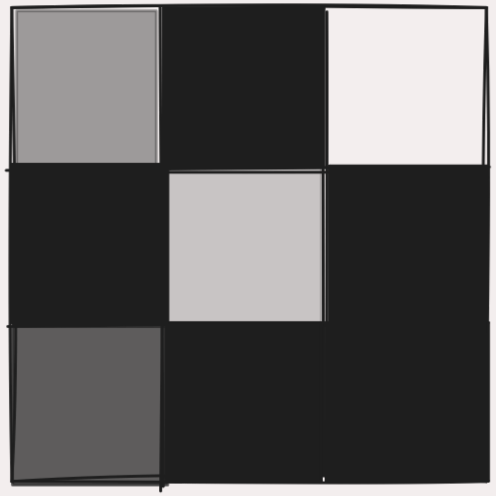
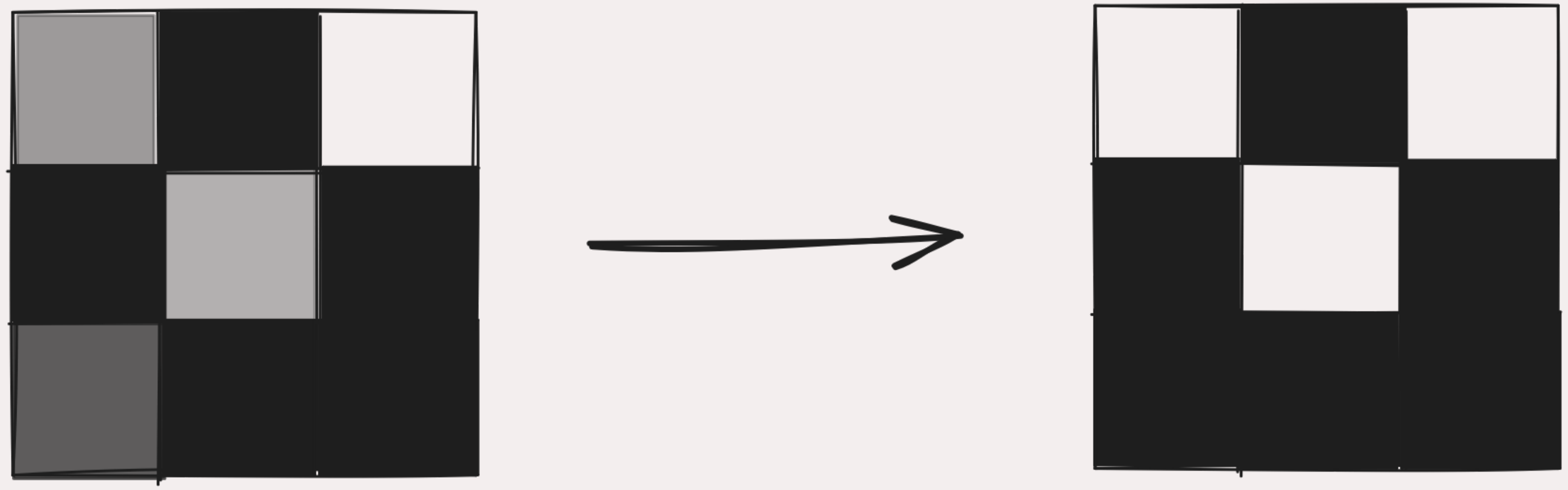

Images as Tensors

- Images represented as N-dimensional arrays
  - Two dimensions correspond to X, Y
  - Additional dimensions correspond to color

$$\begin{bmatrix} 120 & 0 & 255 \\ 0 & 230 & 0 \\ 75 & 0 & 0 \end{bmatrix}$$

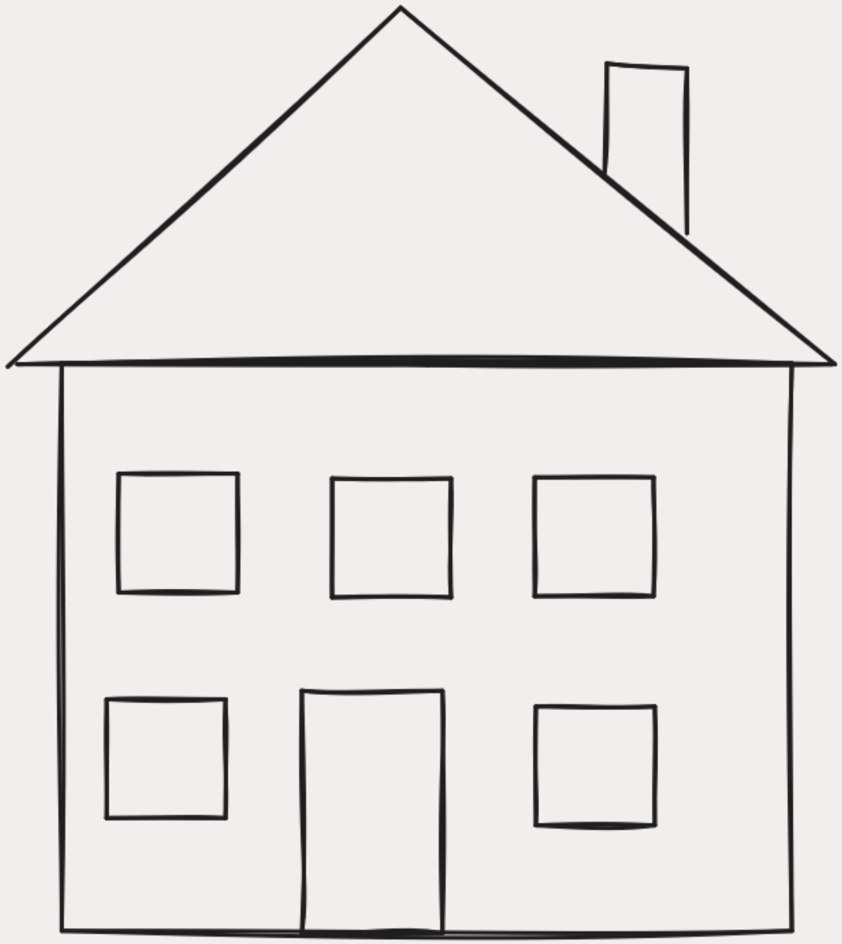


Edge Detection

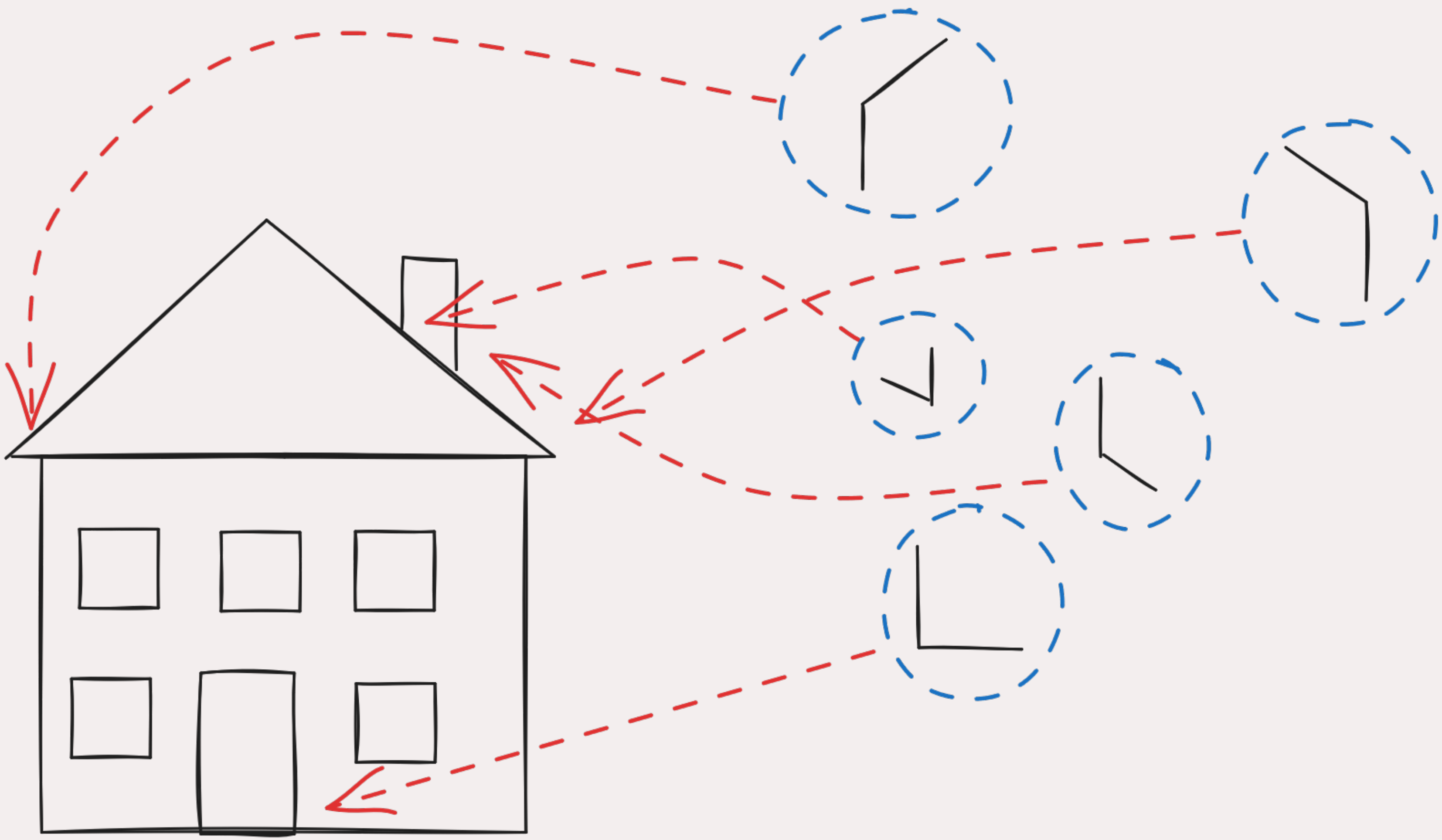


Brick House

Stick House



Features

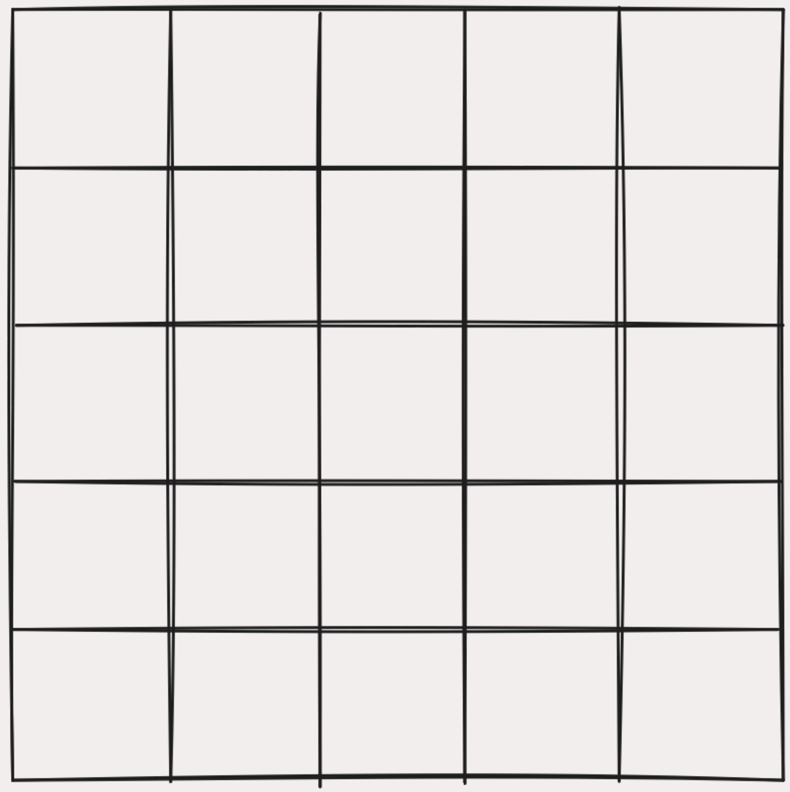


Feature Detection

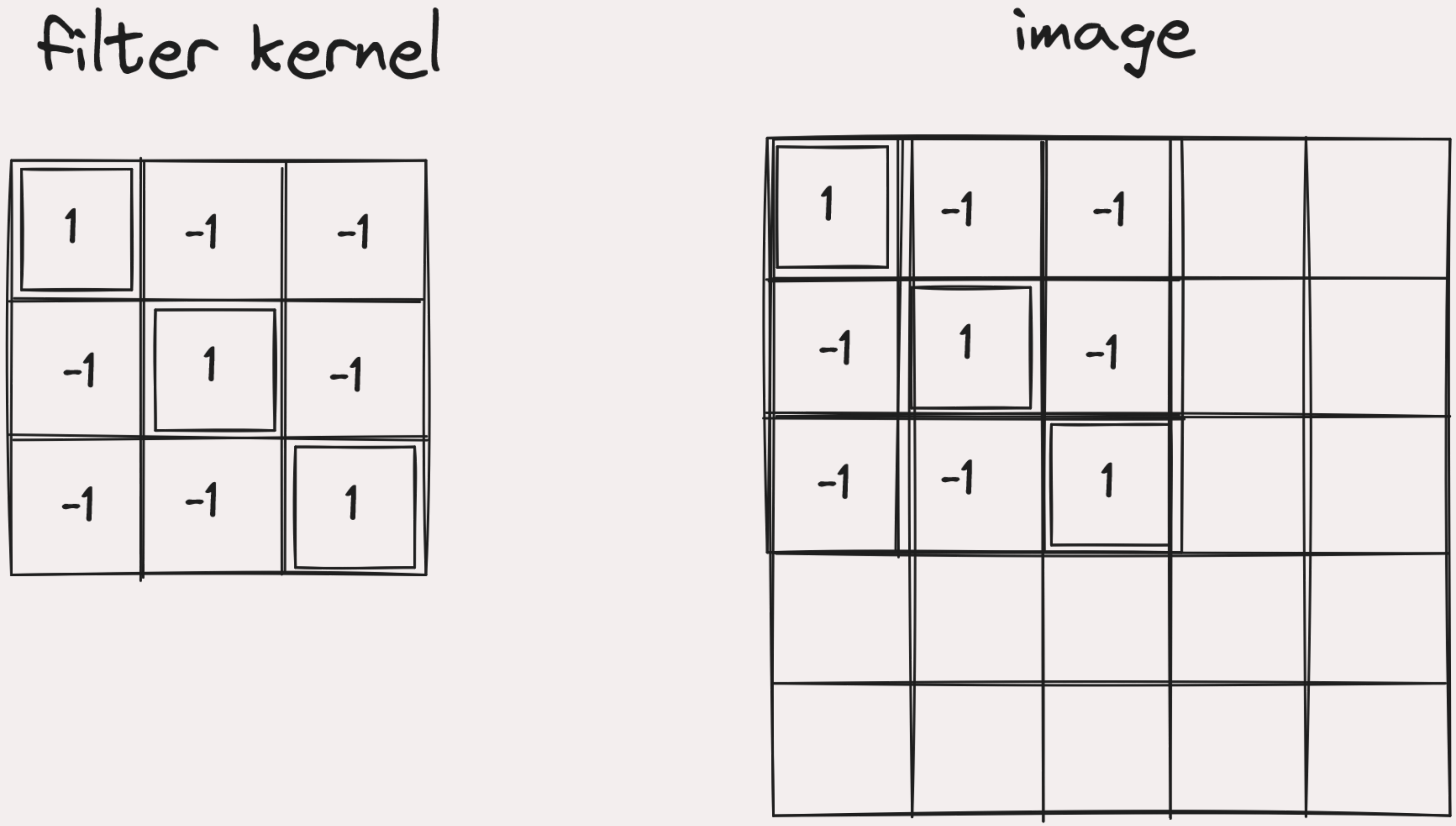
filter kernel

1	-1	-1
-1	1	-1
-1	-1	1

image



Feature Detection



Feature Detection

filter kernel

1	-1	-1
-1	1	-1
-1	-1	1

image

	1	-1	-1	
	-1	1	-1	
	-1	-1	1	

Feature Detection

filter kernel

1	-1	-1
-1	1	-1
-1	-1	1

image

		1	-1	-1
		-1	1	-1
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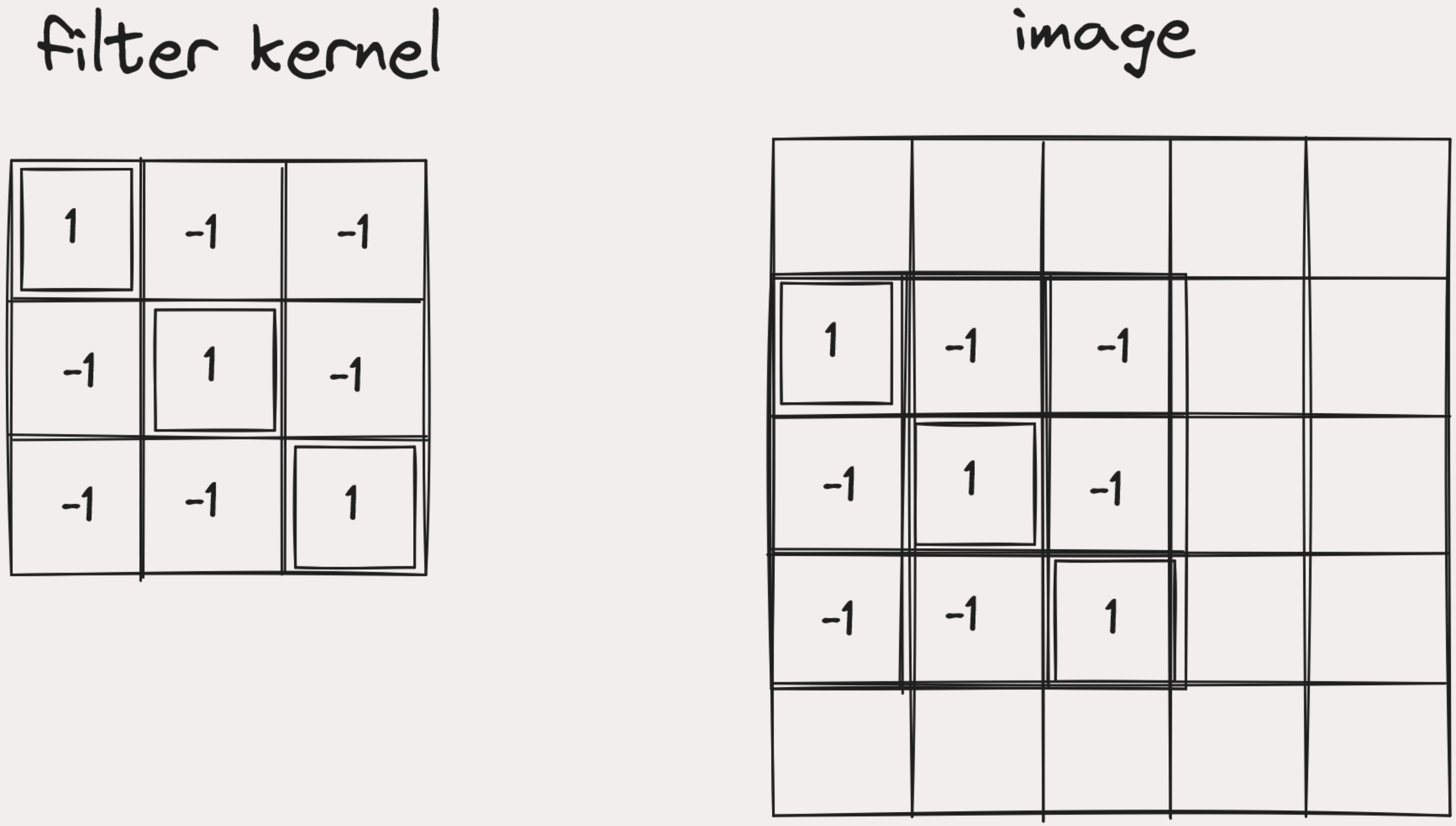
Feature Detection



Feature Detection

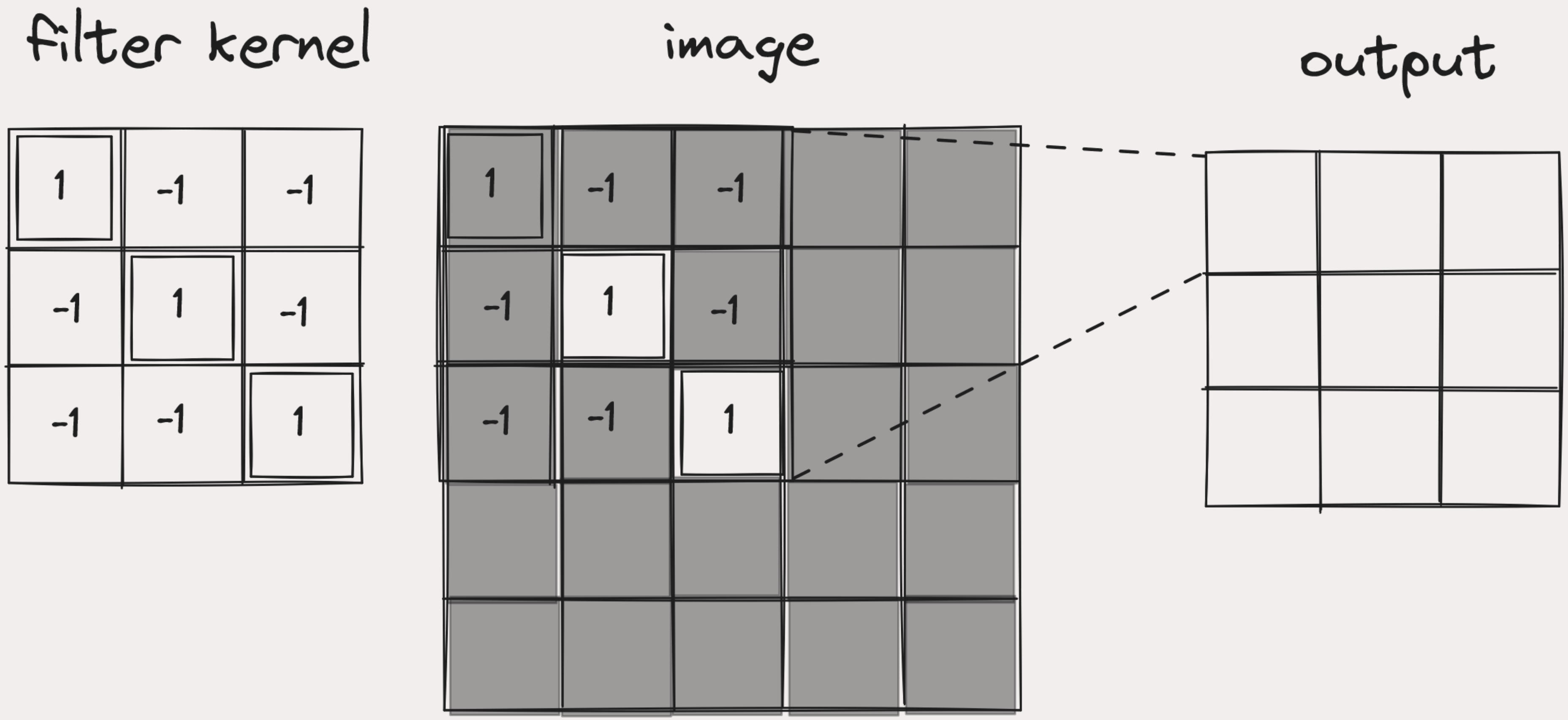
filter kernel

1	-1	-1
-1	1	-1
-1	-1	1

image

0	0	0	0	0
0	255	0	0	0
0	0	255	0	0
0	0	0	0	0
0	0	0	0	0

Feature Detection



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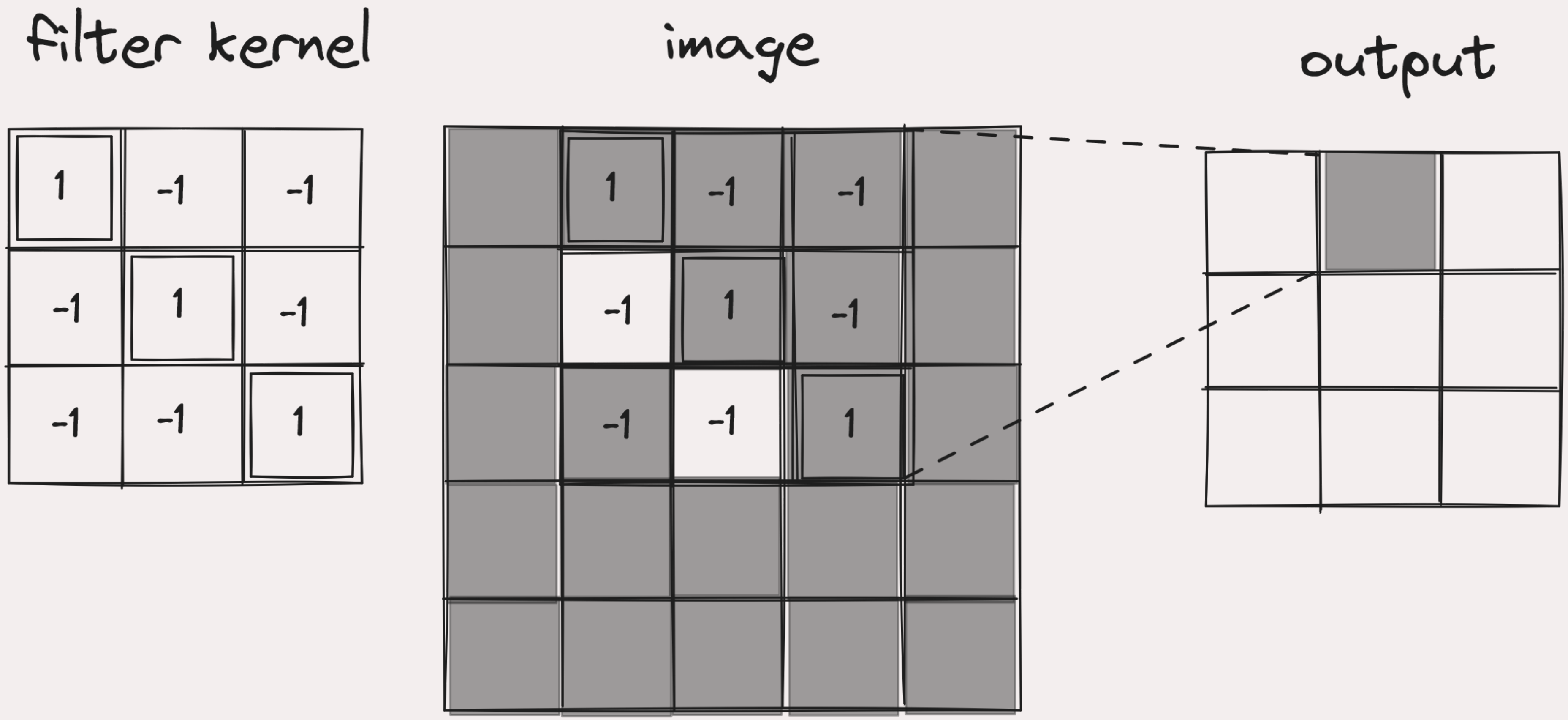

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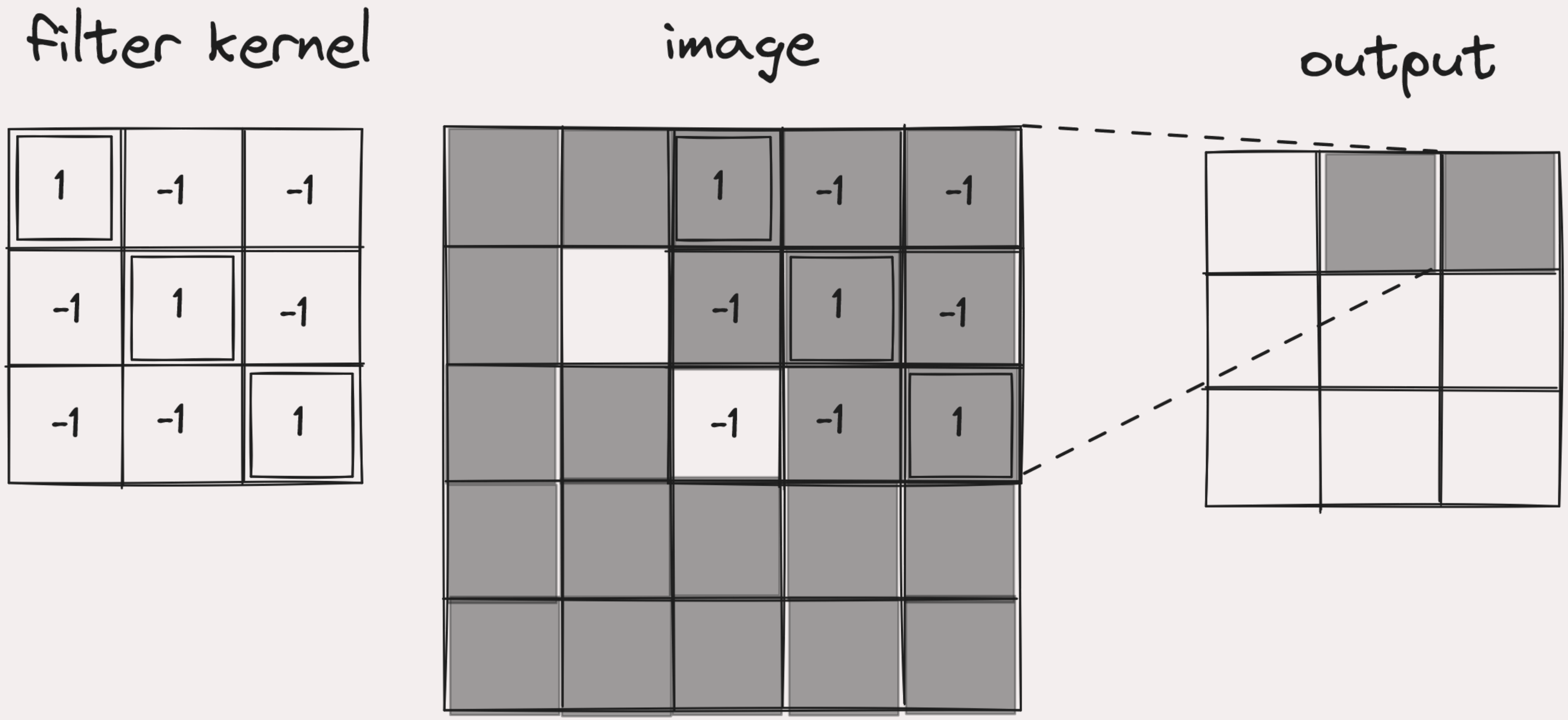

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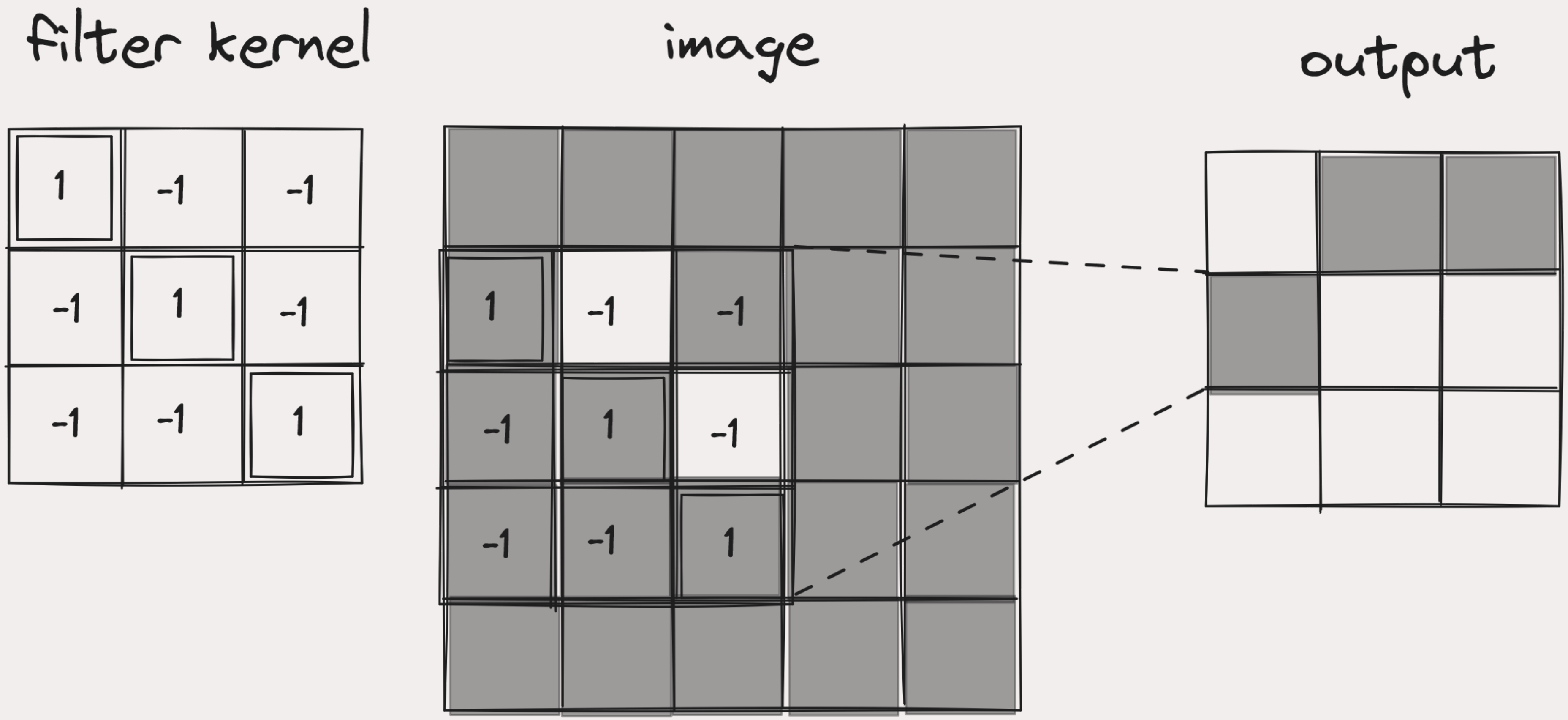

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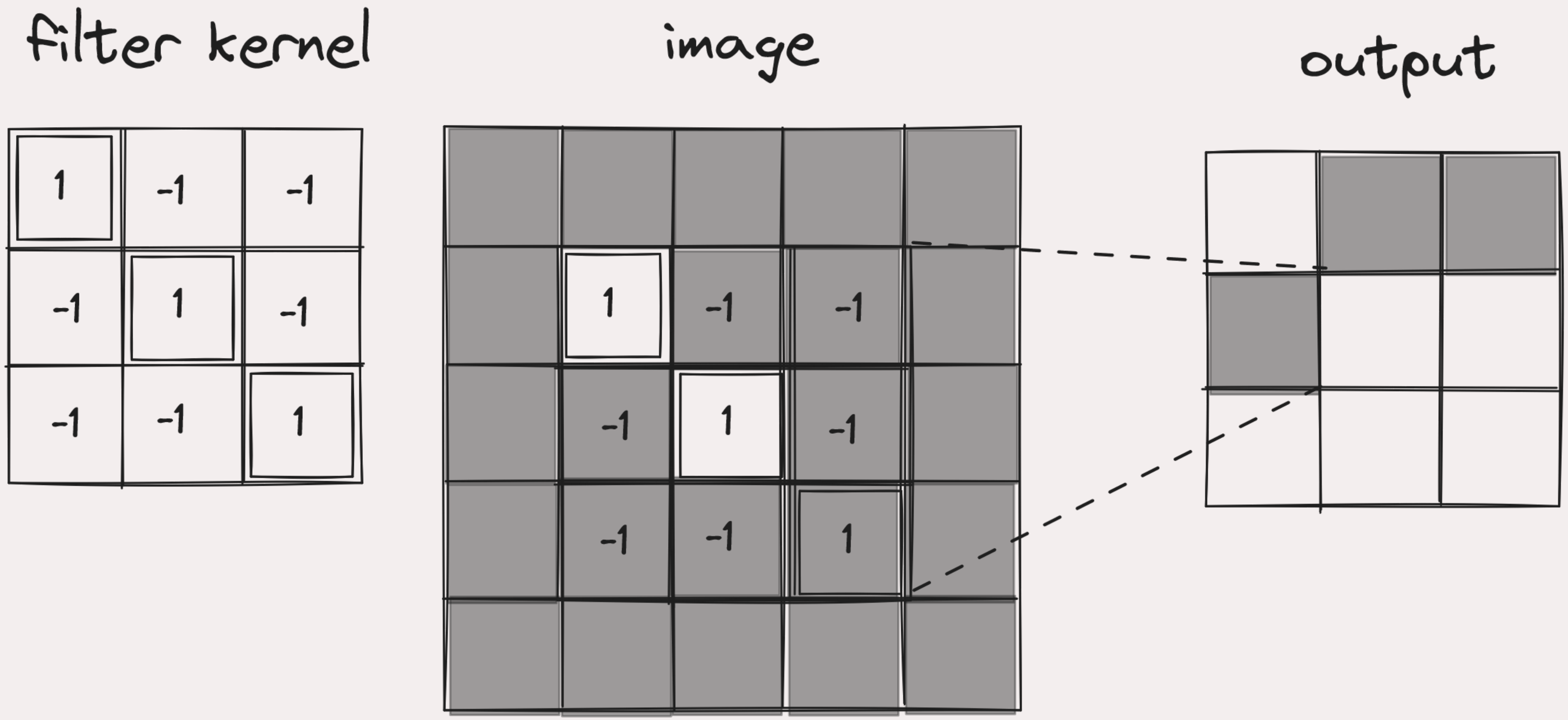

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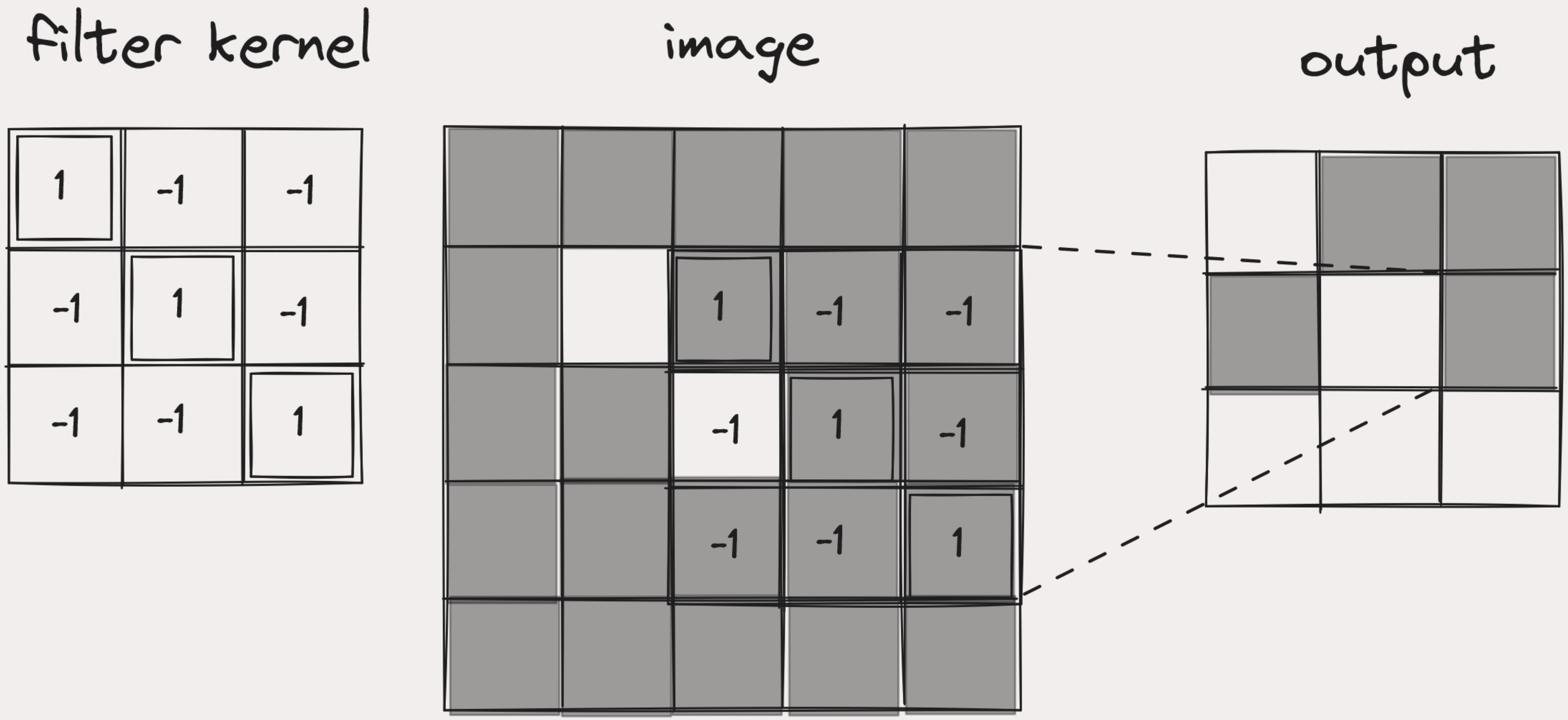
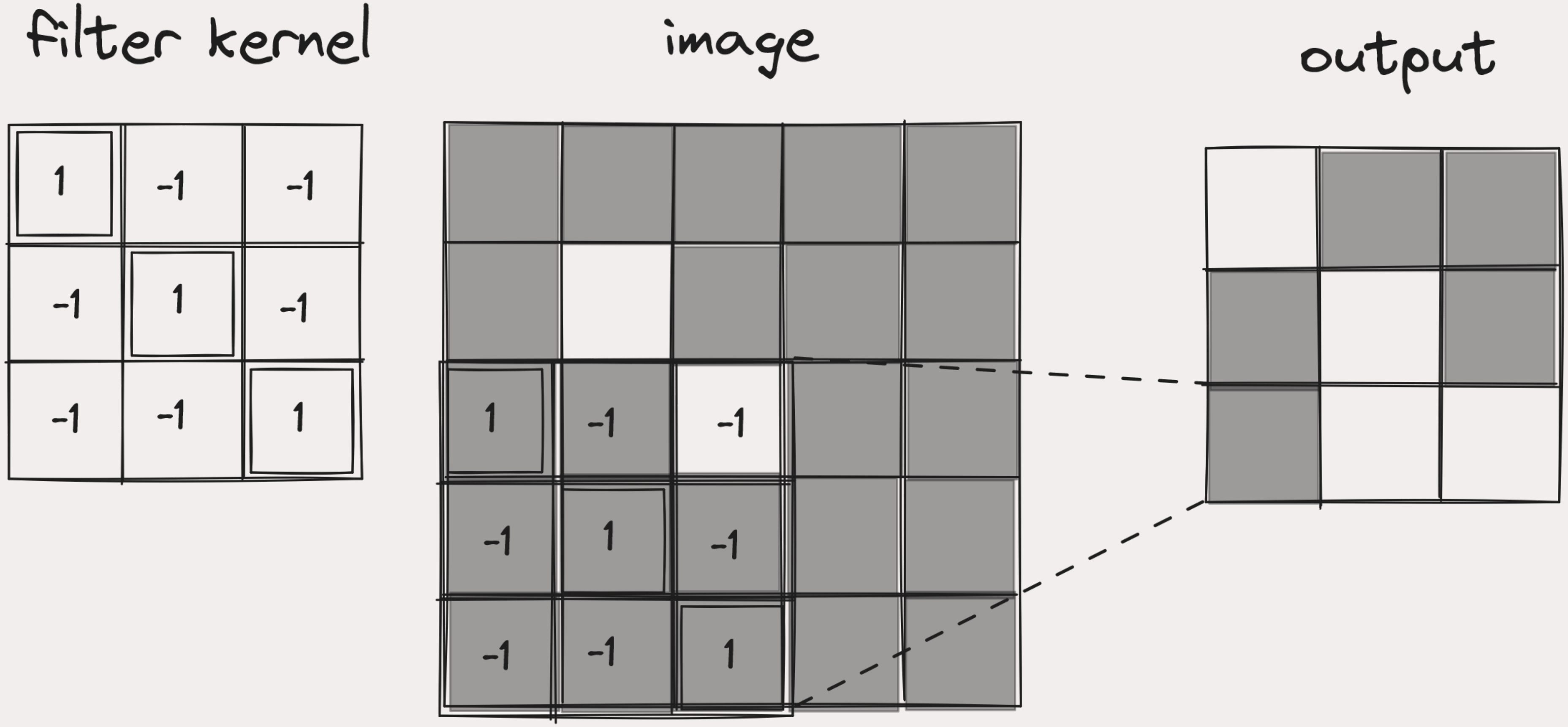


Feature Detection



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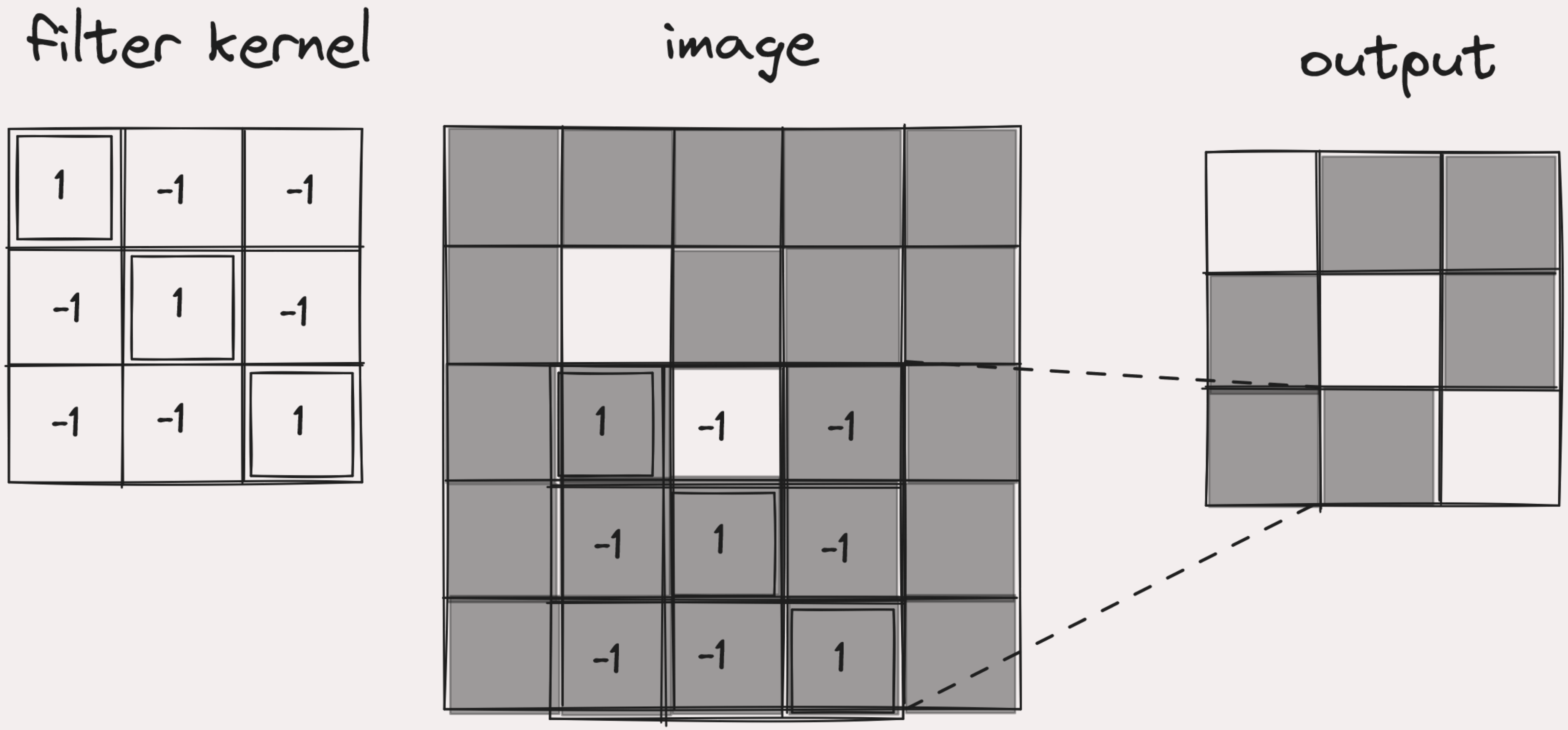

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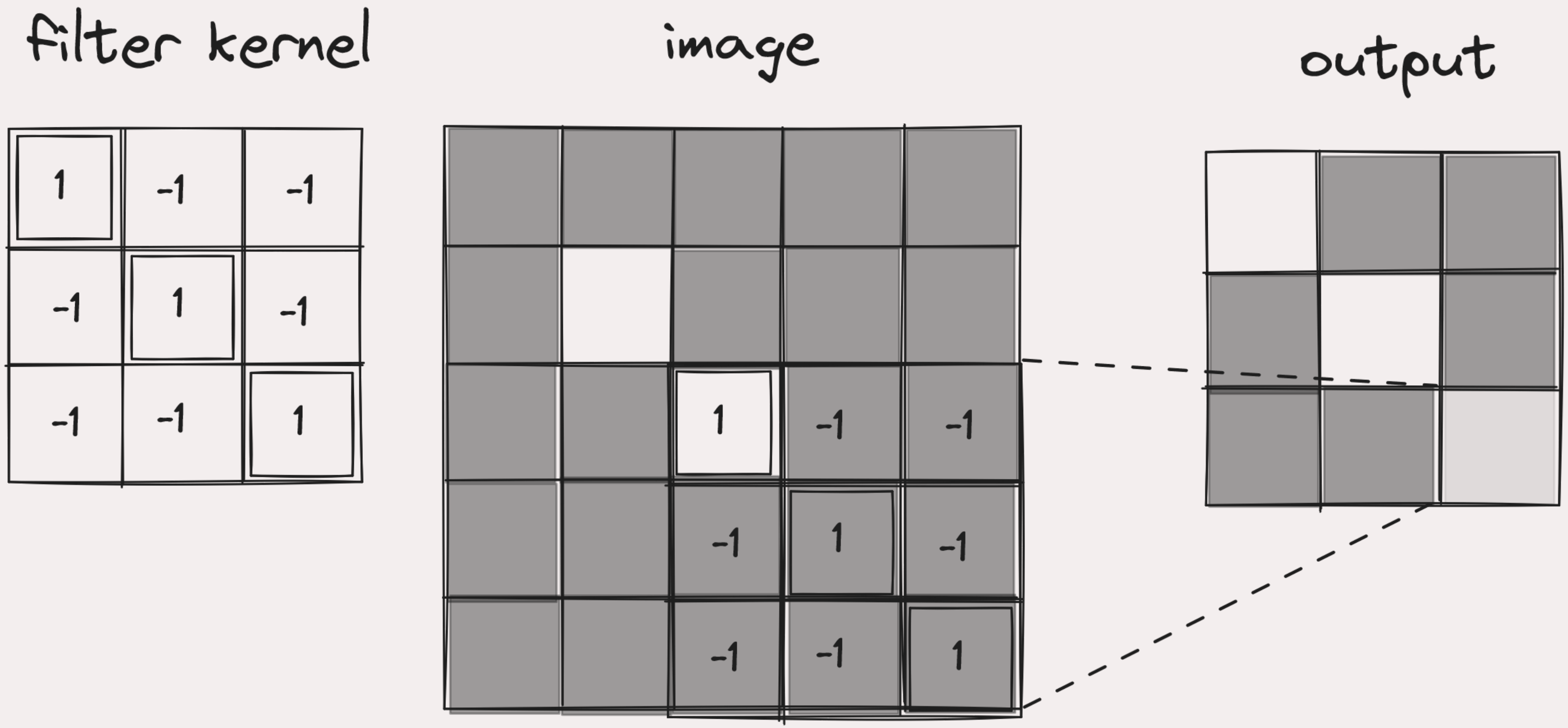
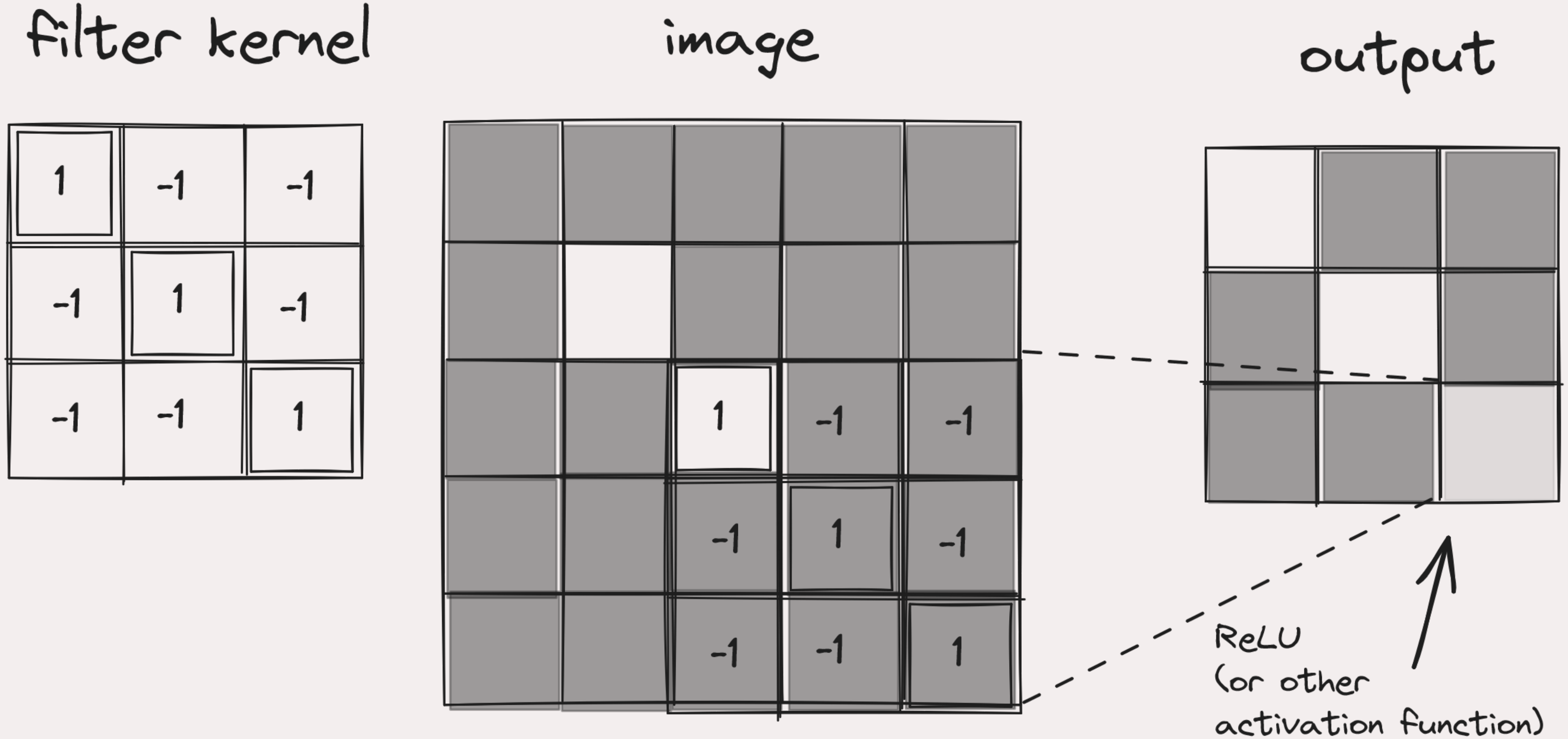
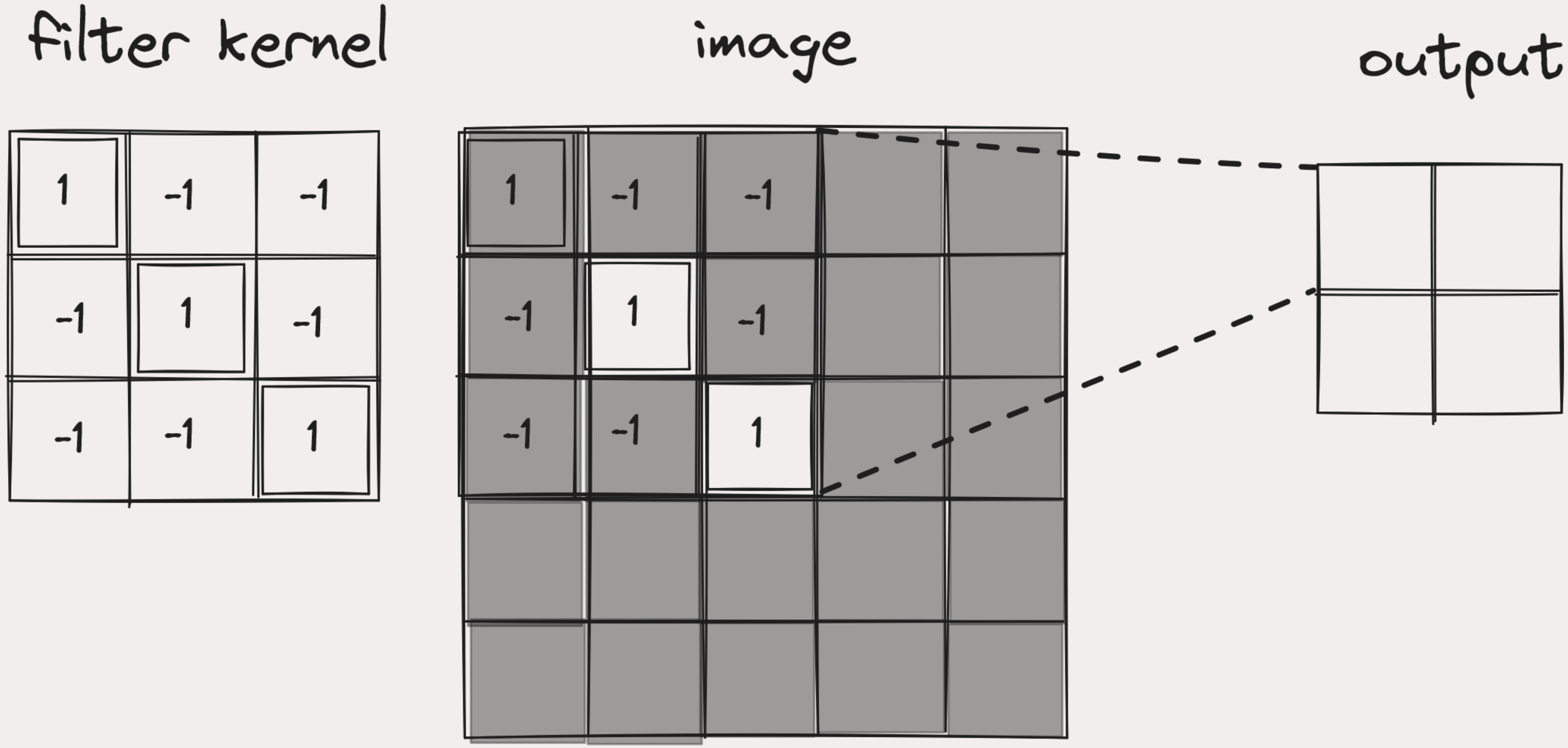


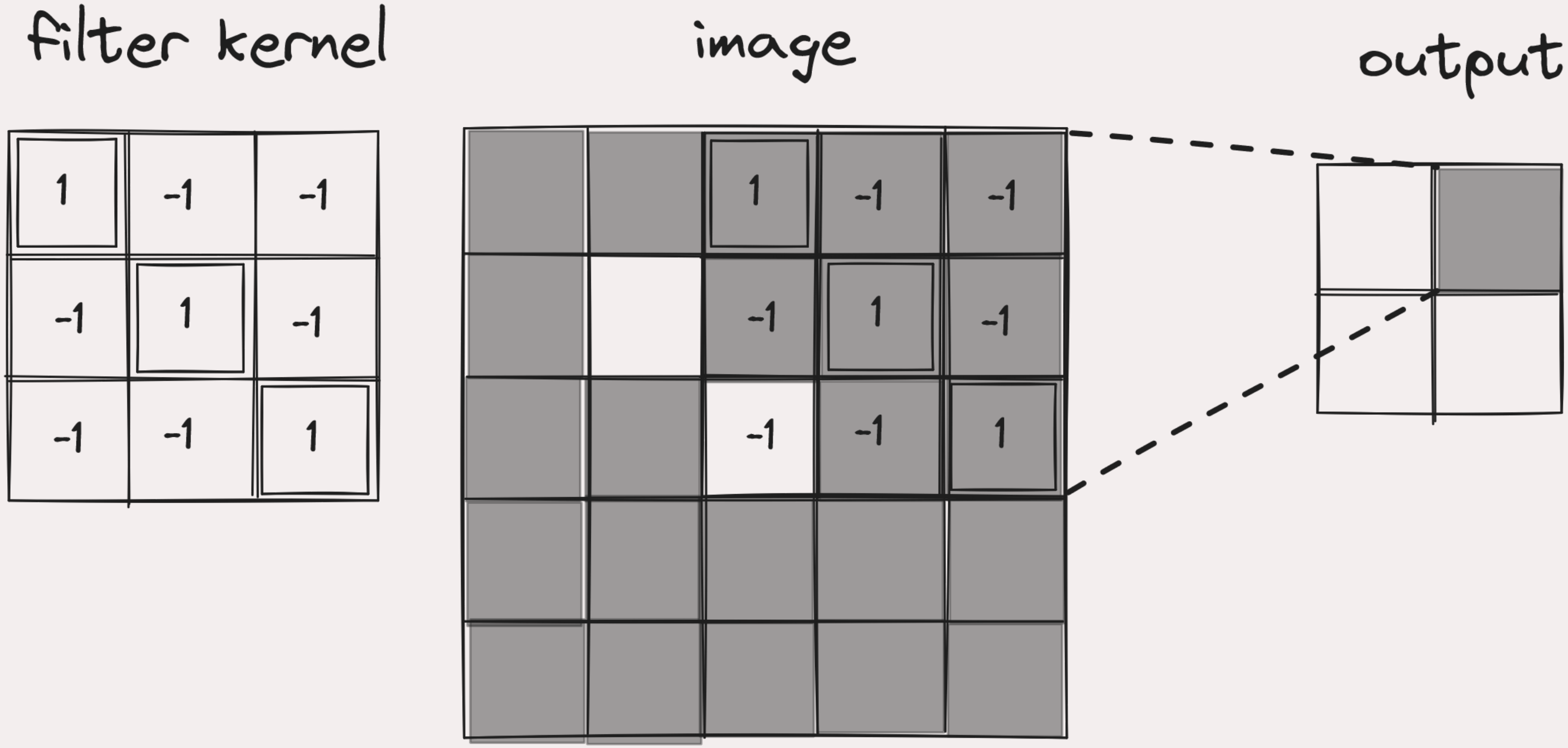
Kernel Activation



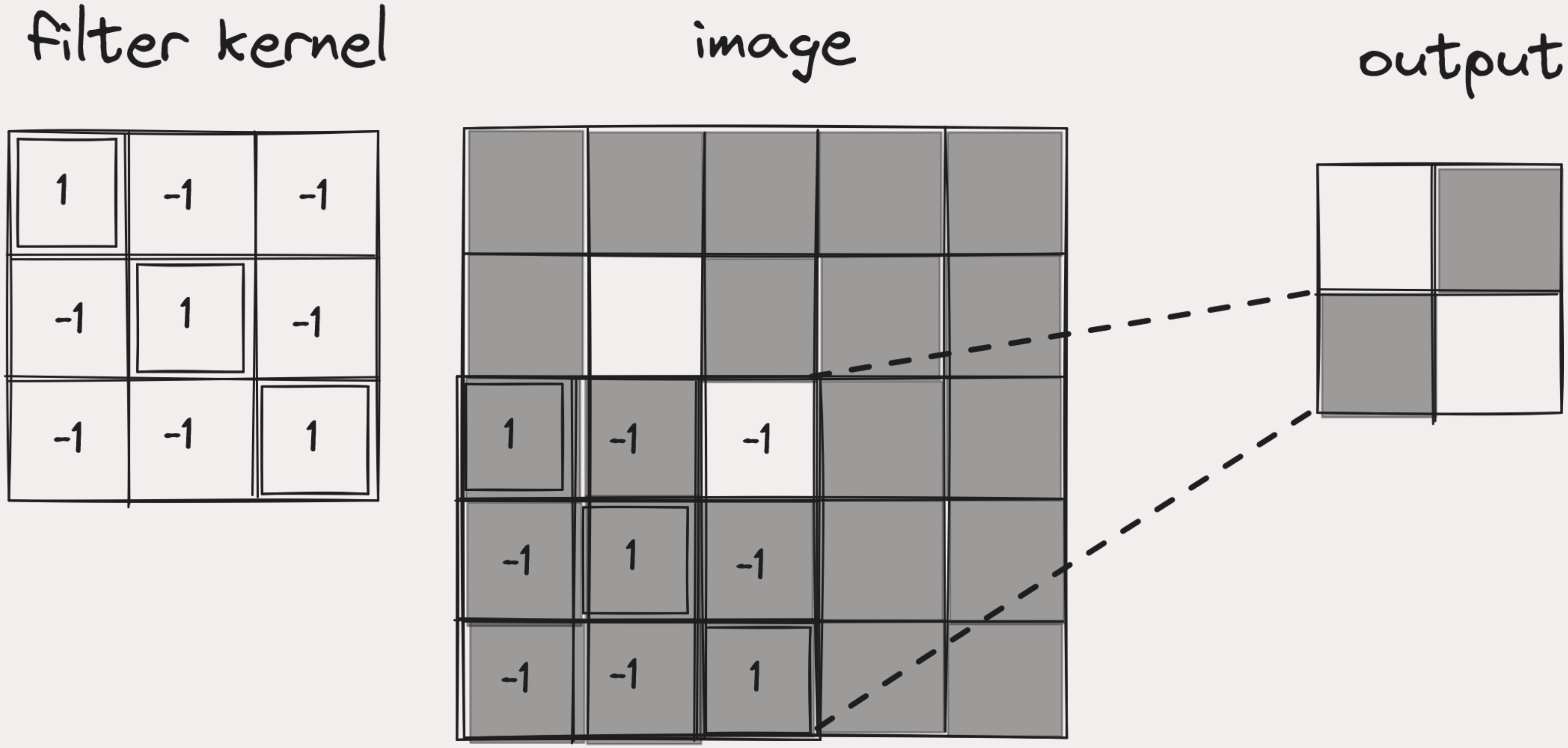
Stride



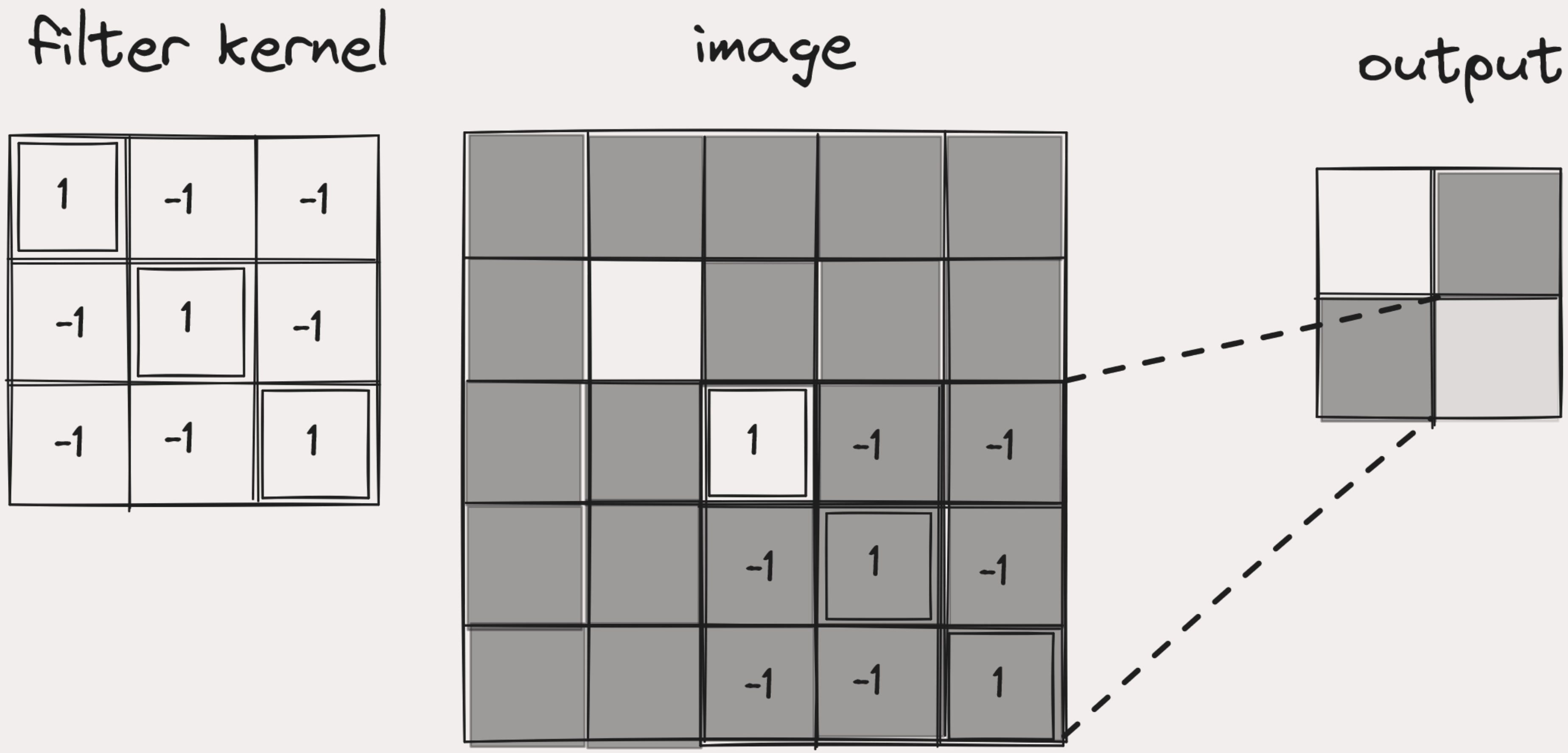
Stride



Stride



Stride

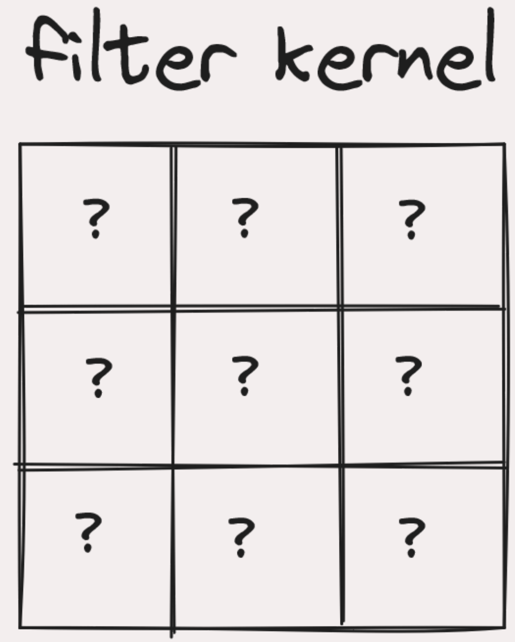


Are we there yet?

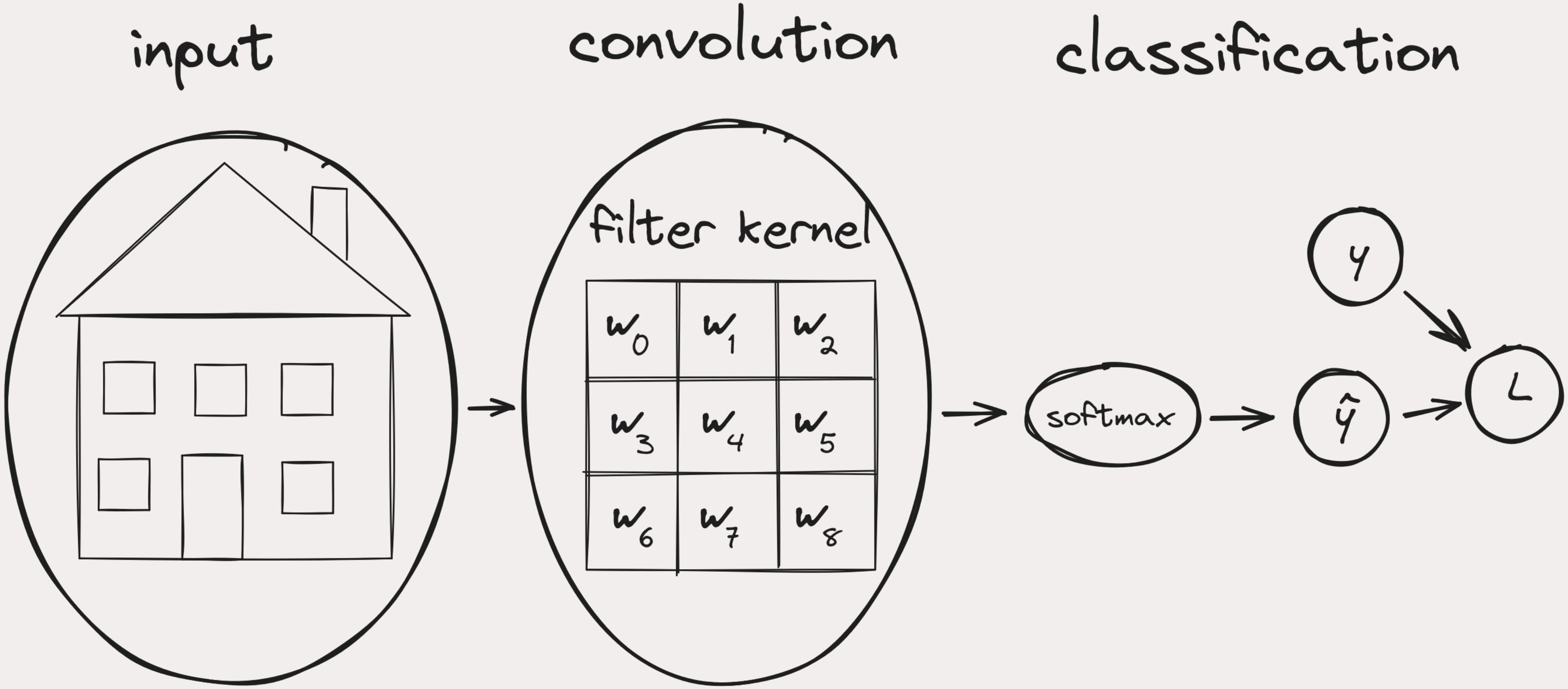
1. Edge Detection
2. Feature Detection
3. ????
4. Profit (ostensibly)

3. ????

- Where do these kernels come from?
- What features are we looking for?
- What is the classification task?



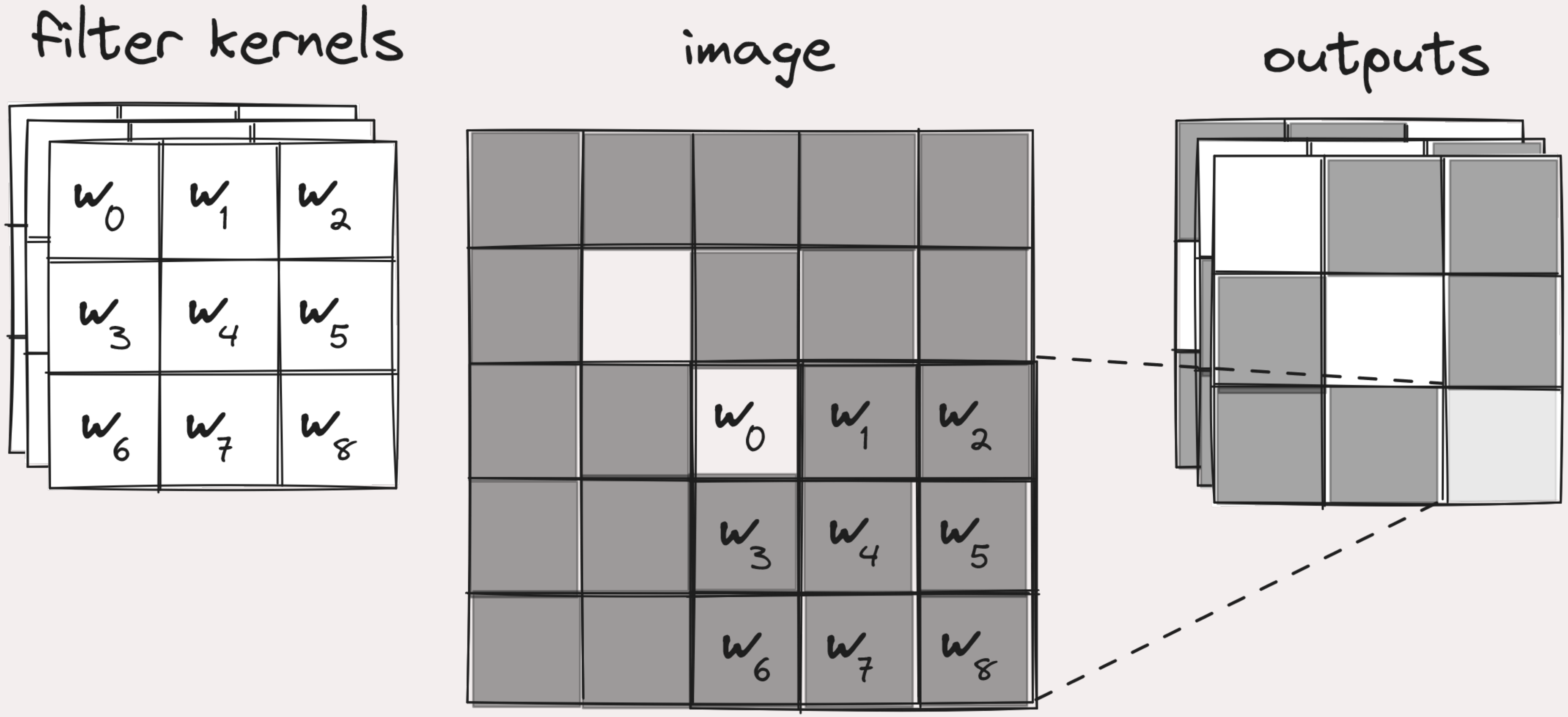
Convolutional Neural Network



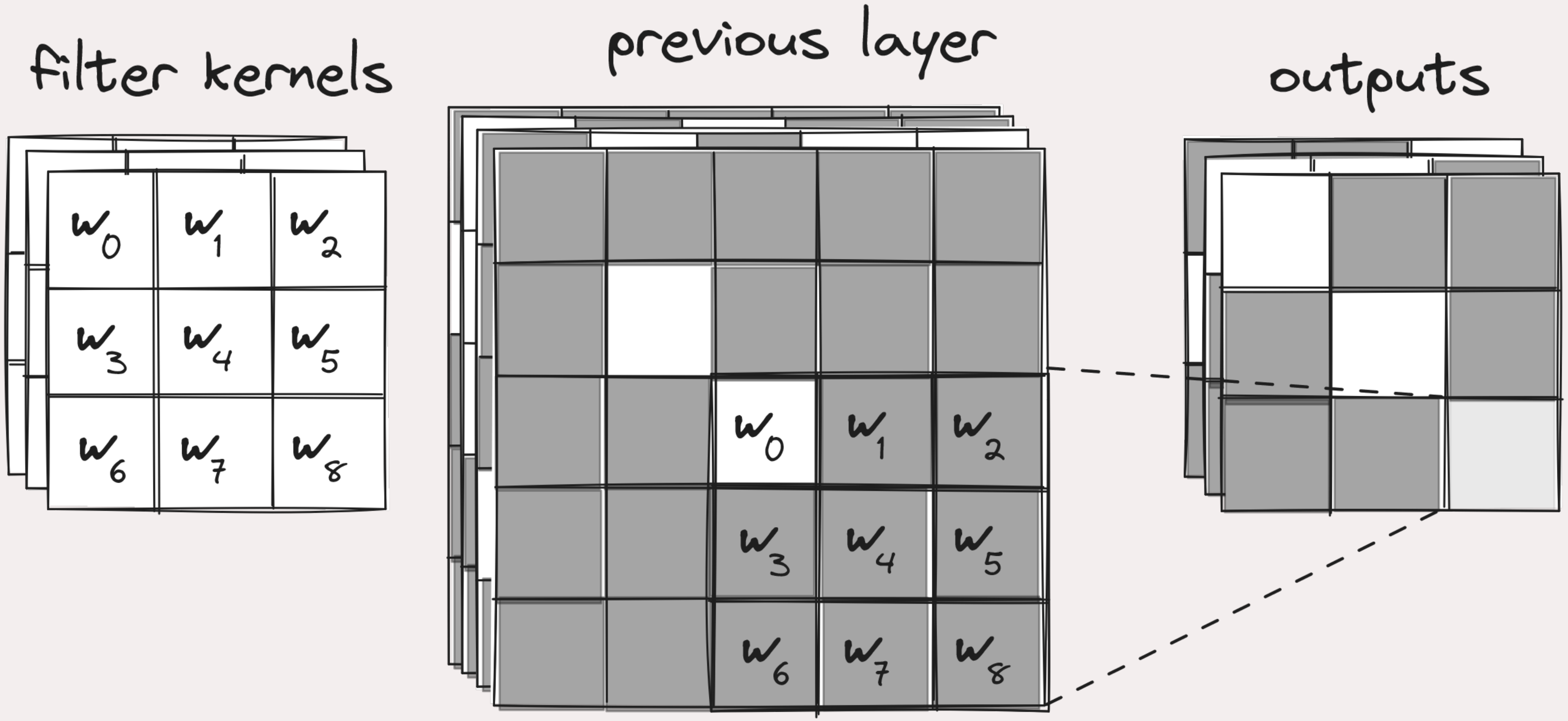
More Filters

- One filter $\rightarrow$ one transformation
  - Edge detection
  - Feature detection
- Apply many filters *in parallel*

More Filters

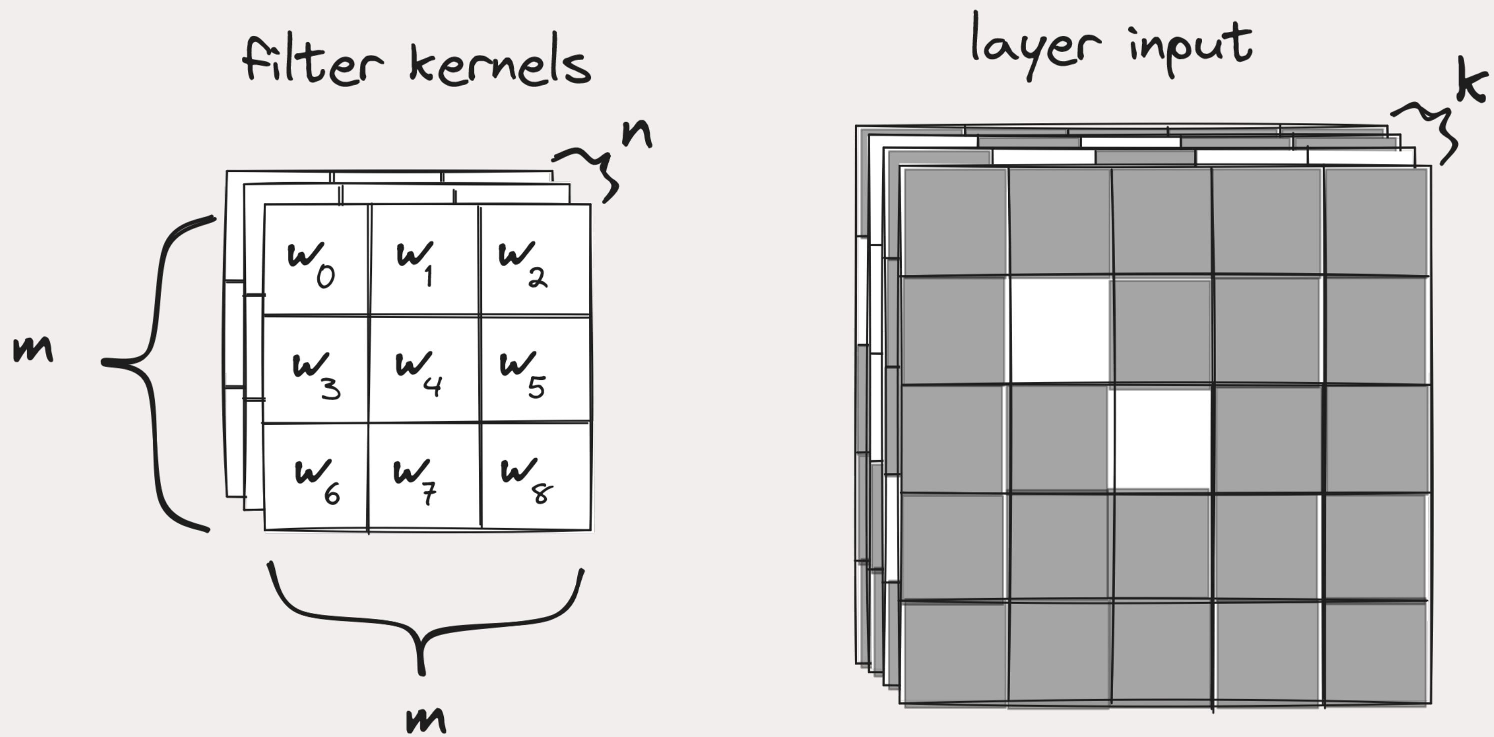


More Layers



filter kernels
previous layer
outputs
w_0 w_1 w_2
w_3 w_4 w_5
w_6 w_7 w_8
w_0 w_1 w_2
w_3 w_4 w_5
w_6 w_7 w_8

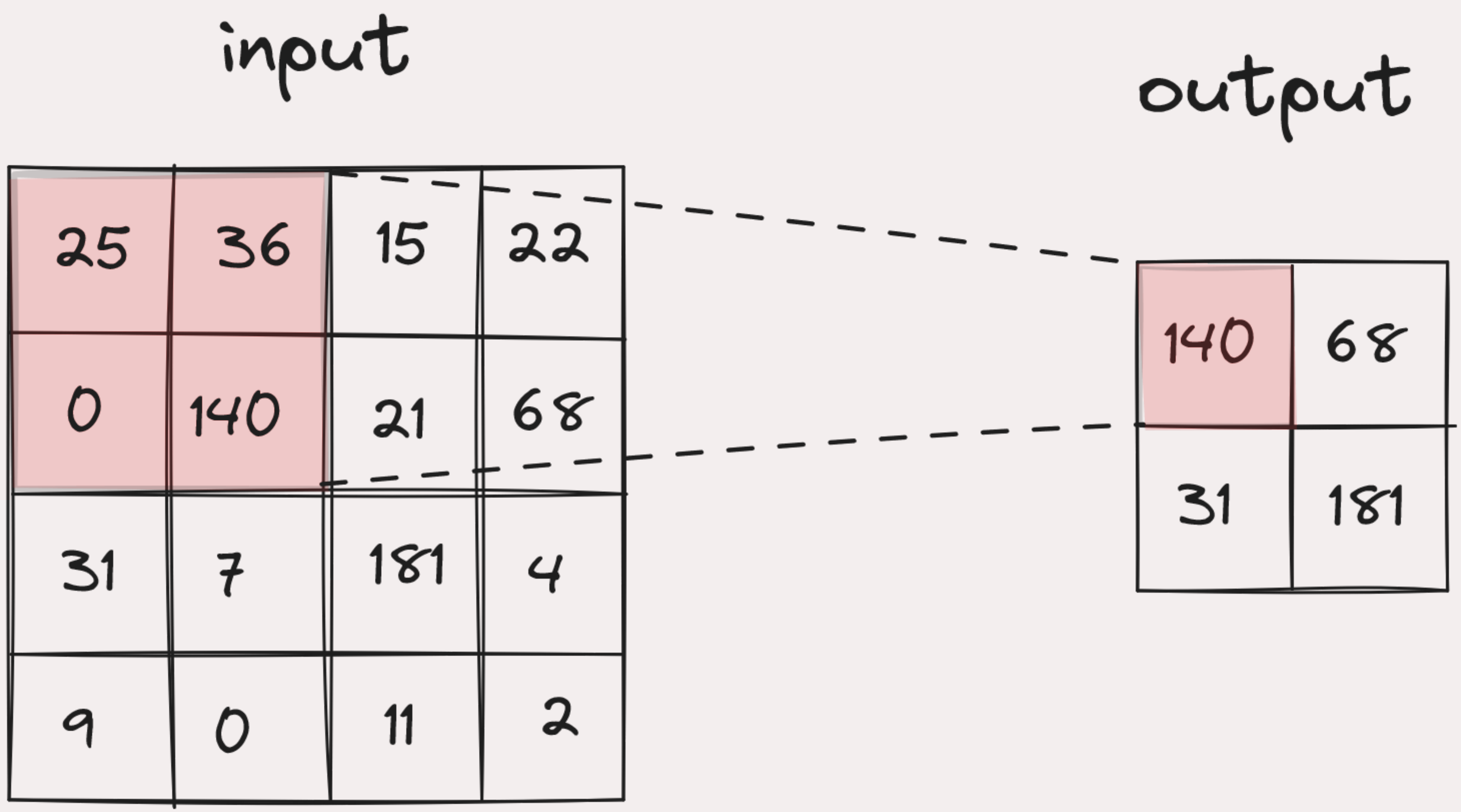
Parameter Explosion



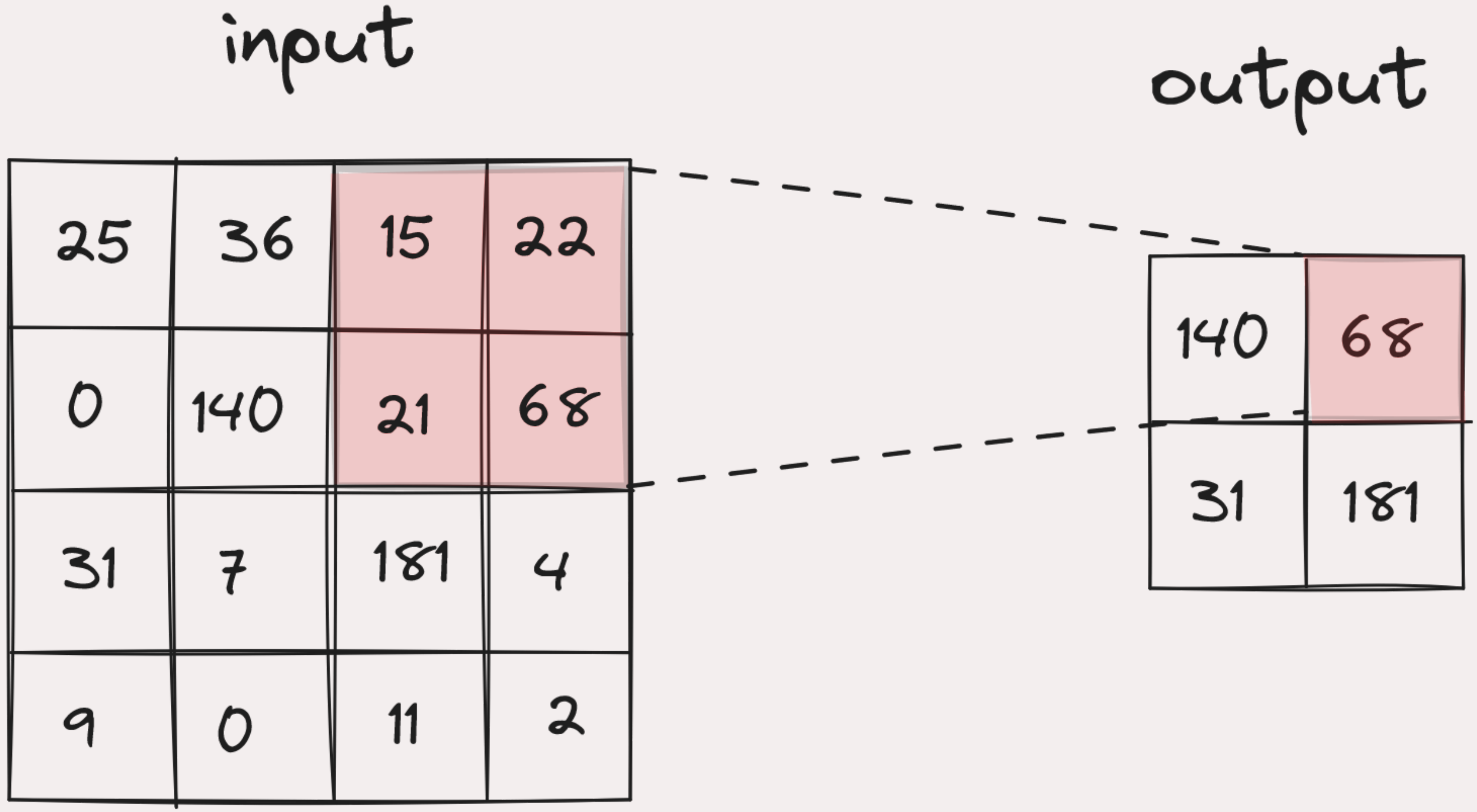
$m \cdot m \cdot n \cdot k$ parameters!

$(m \cdot m \cdot n + 1) \cdot k$ with bias

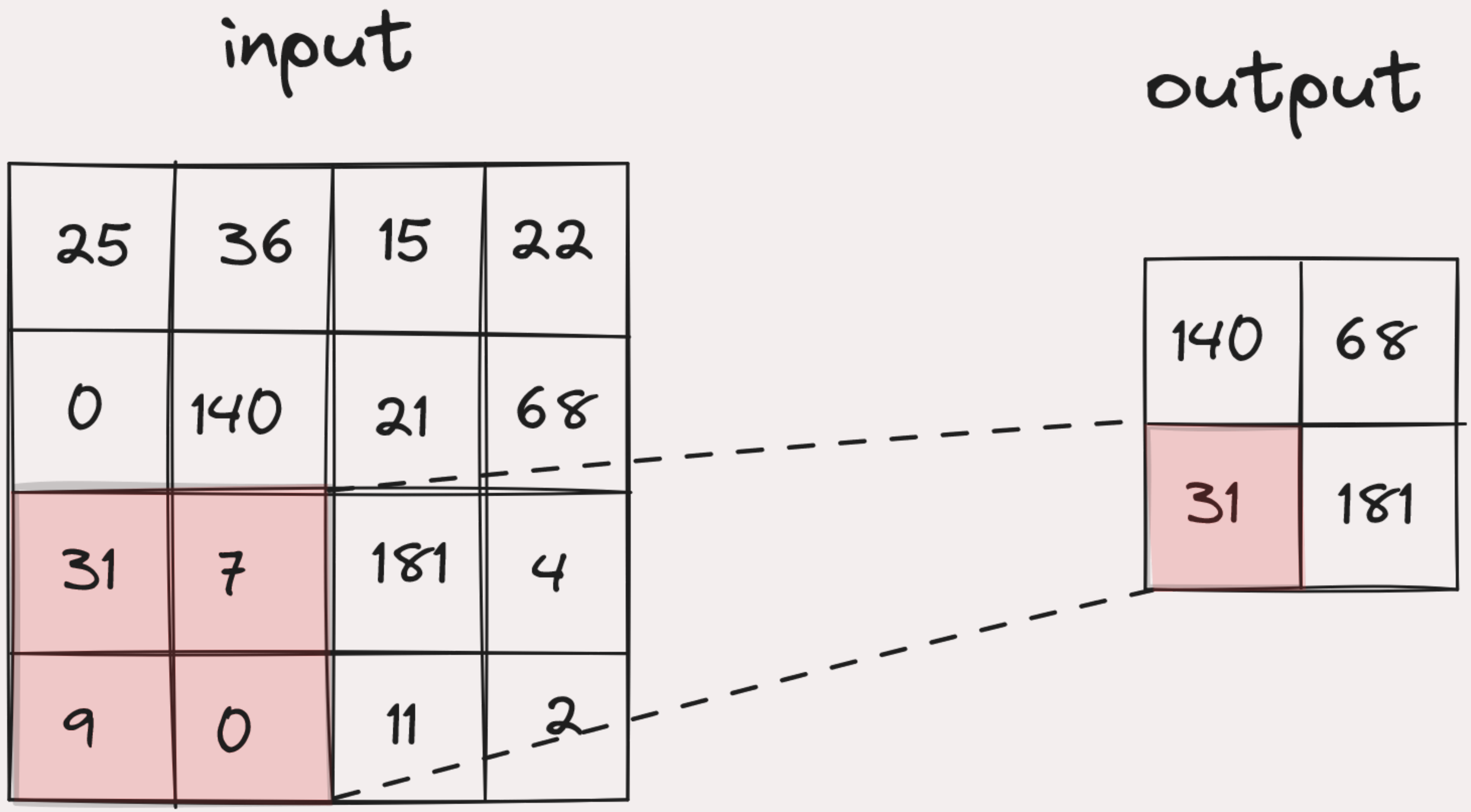
Max Pooling



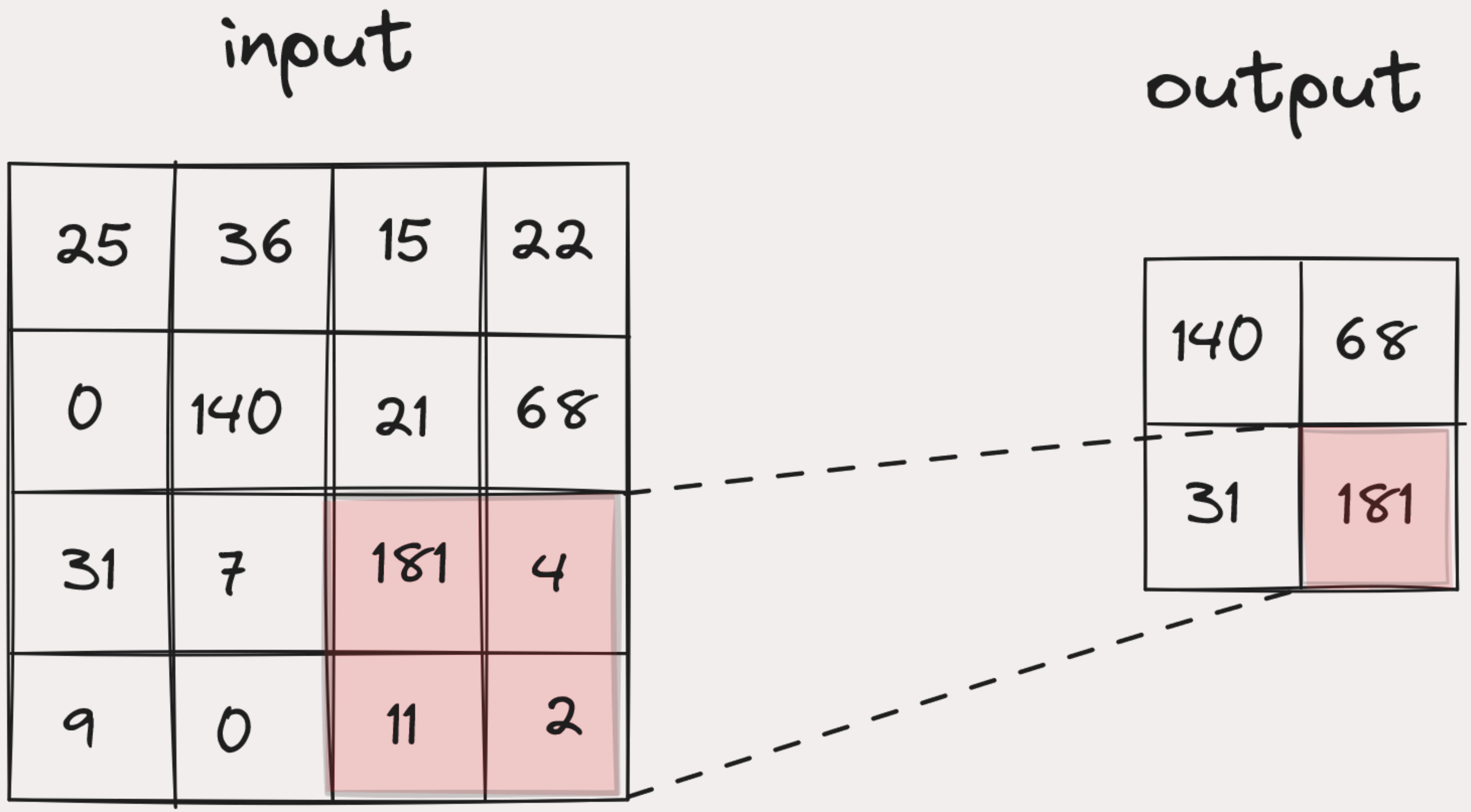
Max Pooling



Max Pooling



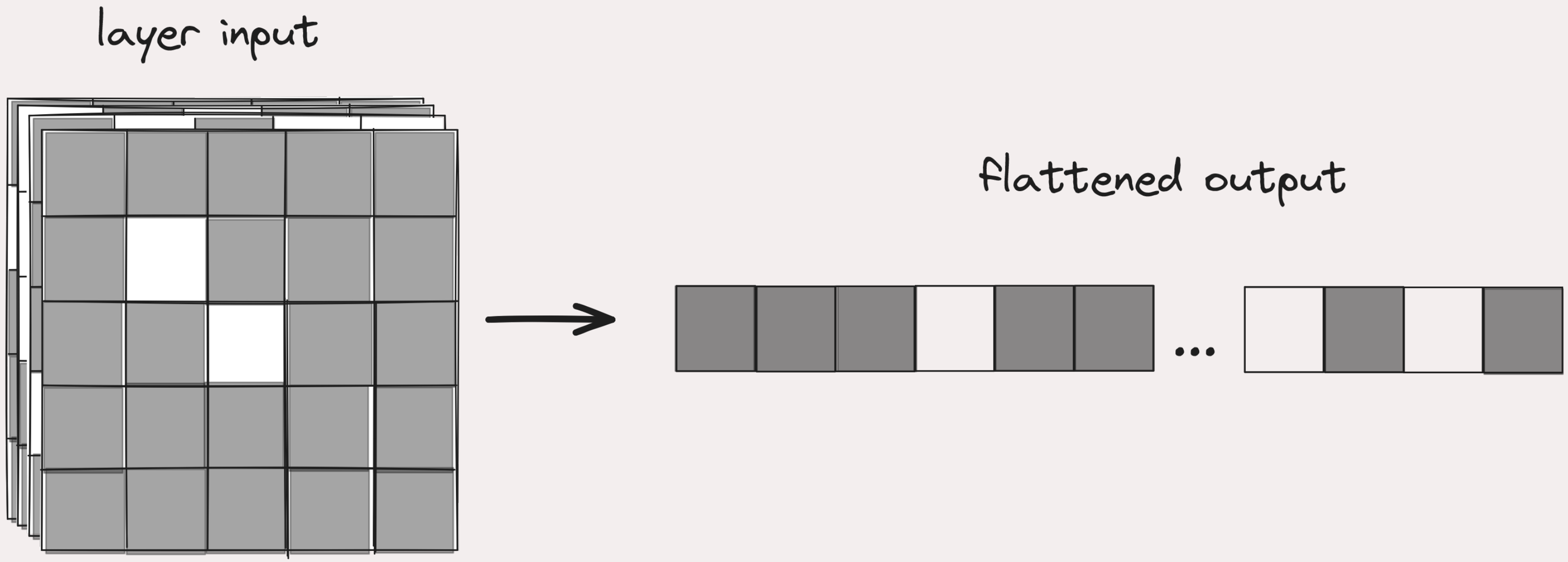
Max Pooling



Max Pooling - Why?

- Translational invariance
    - Model robust to small displacements
- Reduces size of final feature map
- Increases how much of input later layers “see”

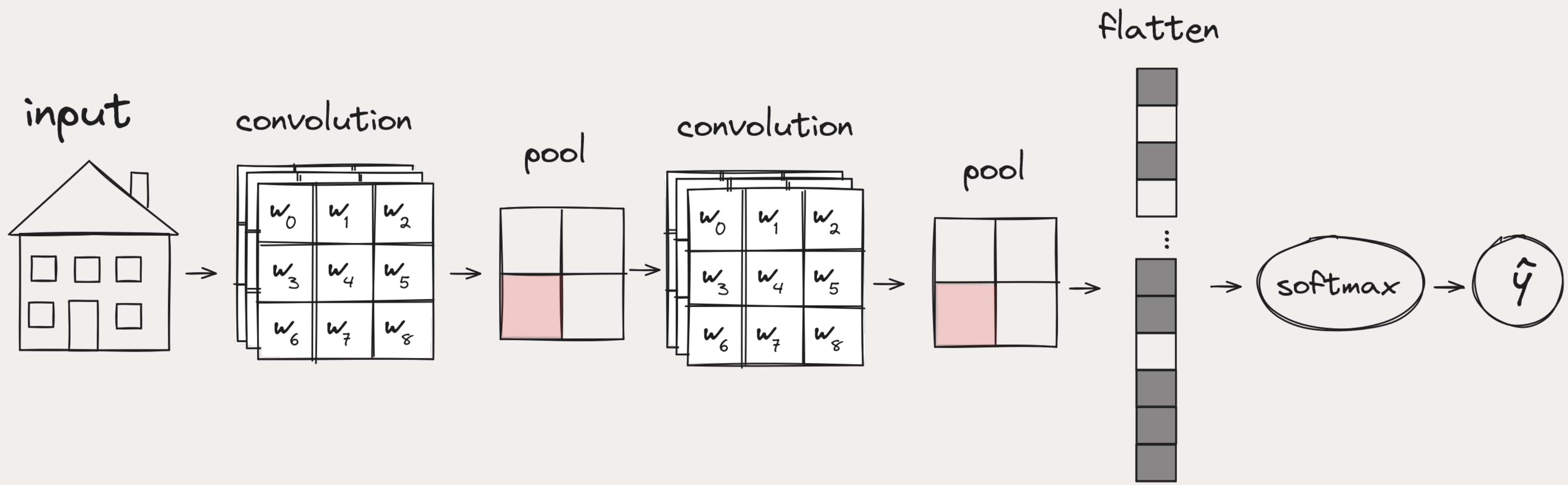
Flattening Time



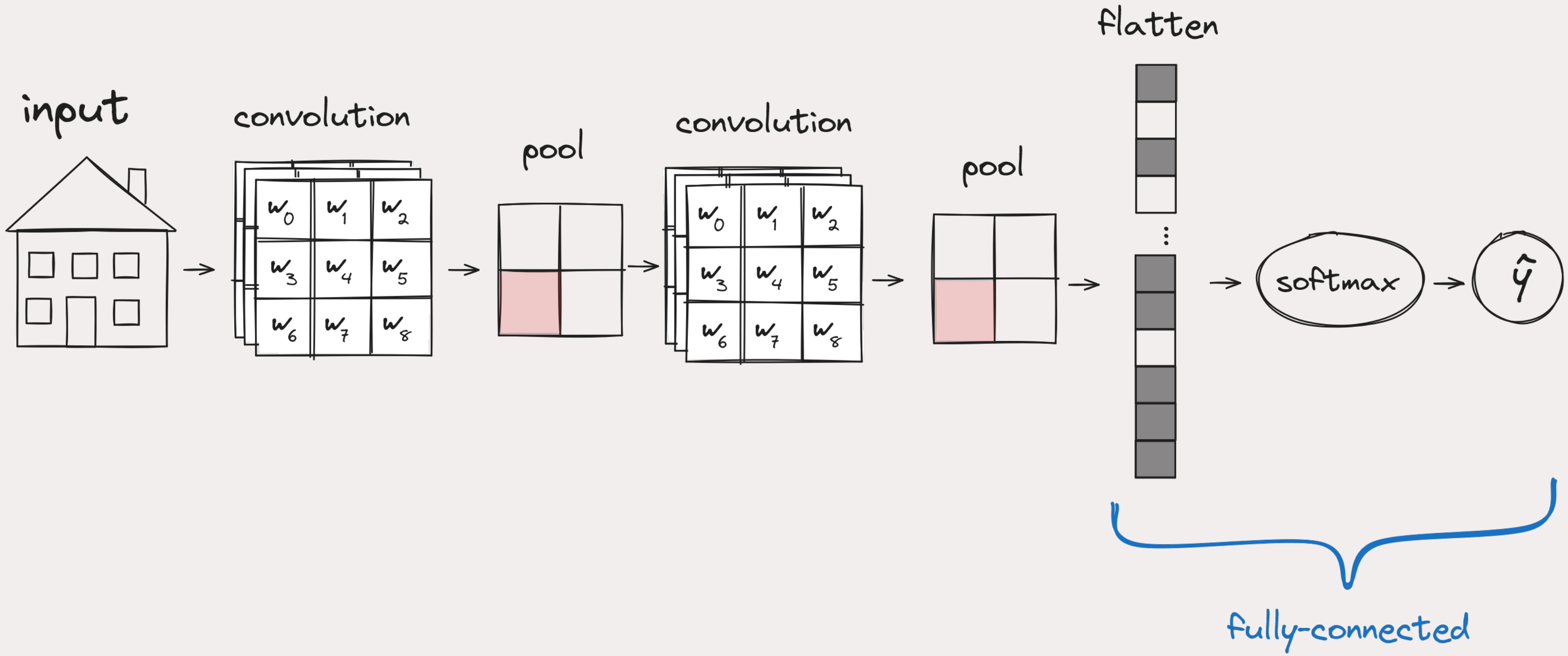
- Prepares for fully-connected classifier output
- "Unpacks" to $1 \times n$ tensor[1]

1. For standard classifier – *not* for YOLO

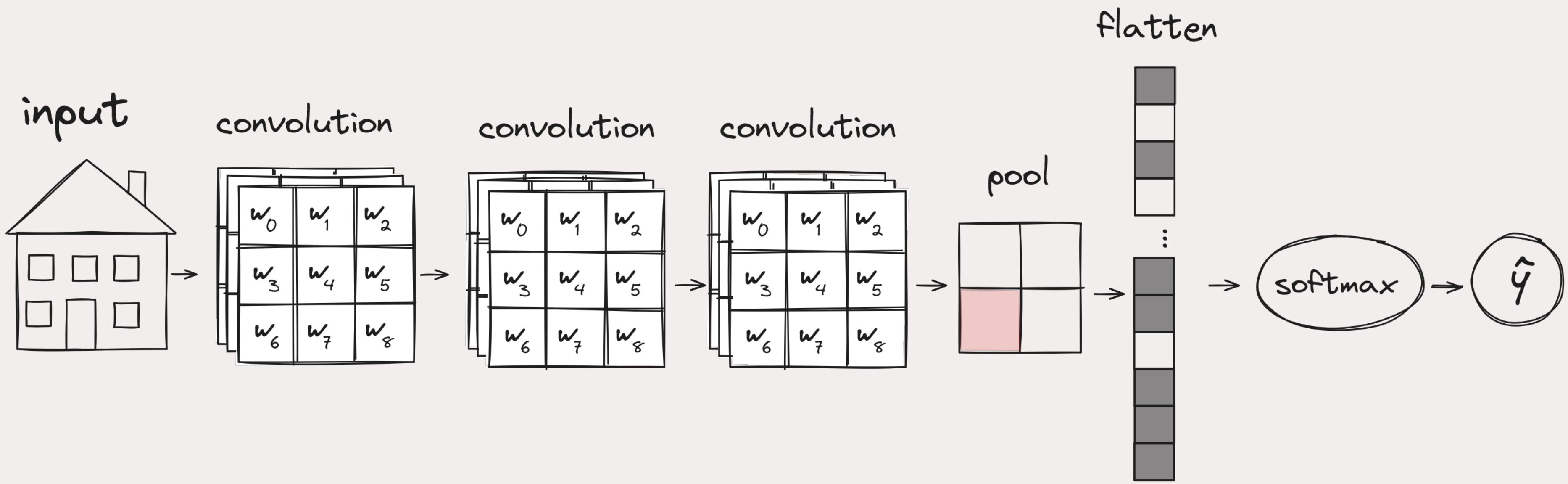
All Together



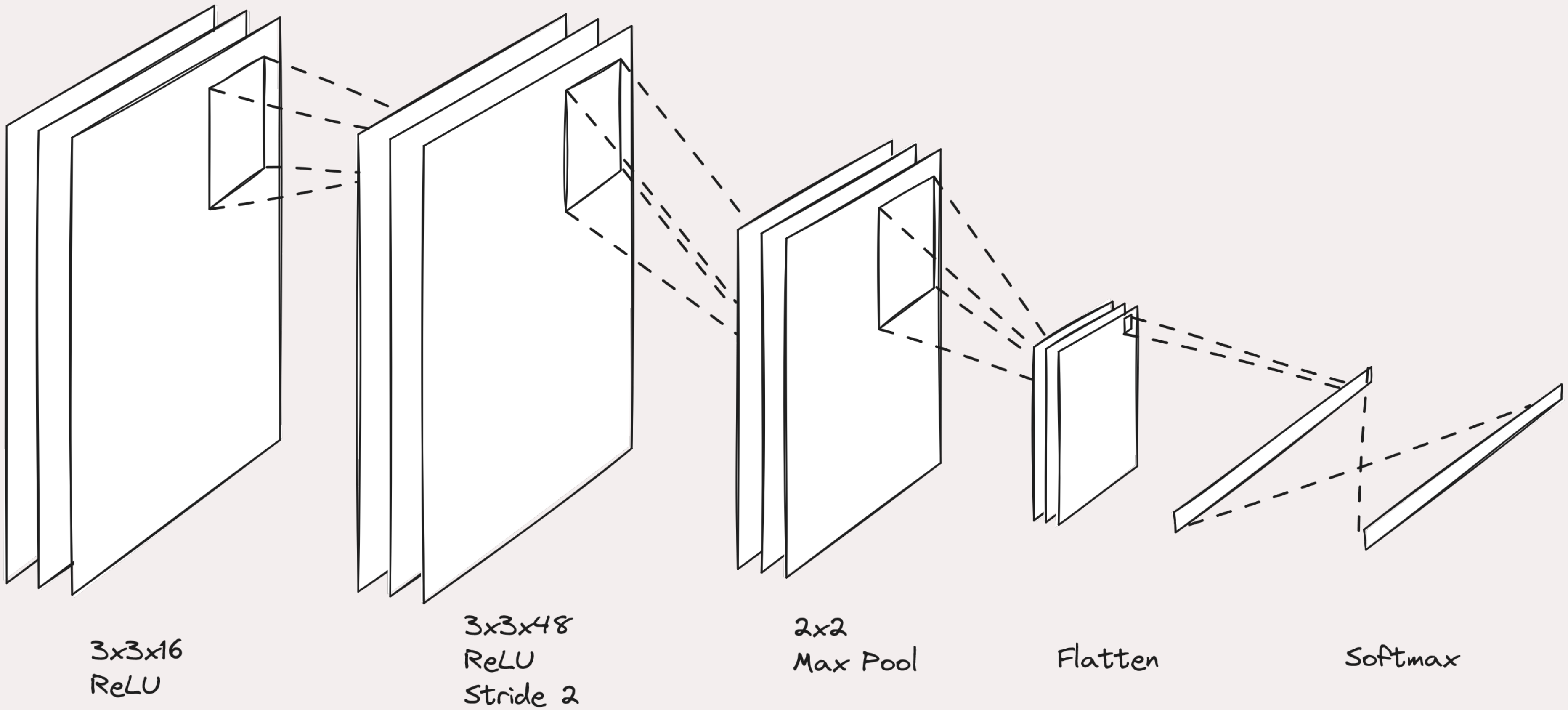
Fully-Connected



Different Architectures



Multiple Representations



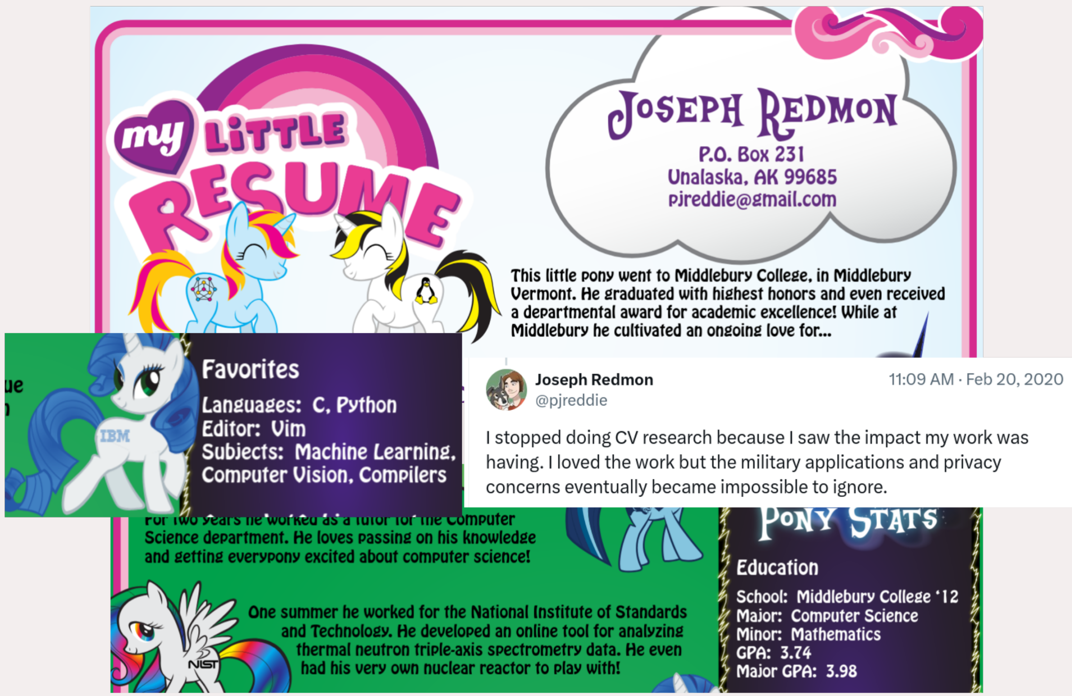
Multiple Representations

Table 1: **ConvNet configurations** (shown in columns). The depth of the configurations increases from the left (A) to the right (E), as more layers are added (the added layers are shown in bold). The convolutional layer parameters are denoted as "conv⟨receptive field size⟩-⟨number of channels⟩". The ReLU activation function is not shown for brevity.

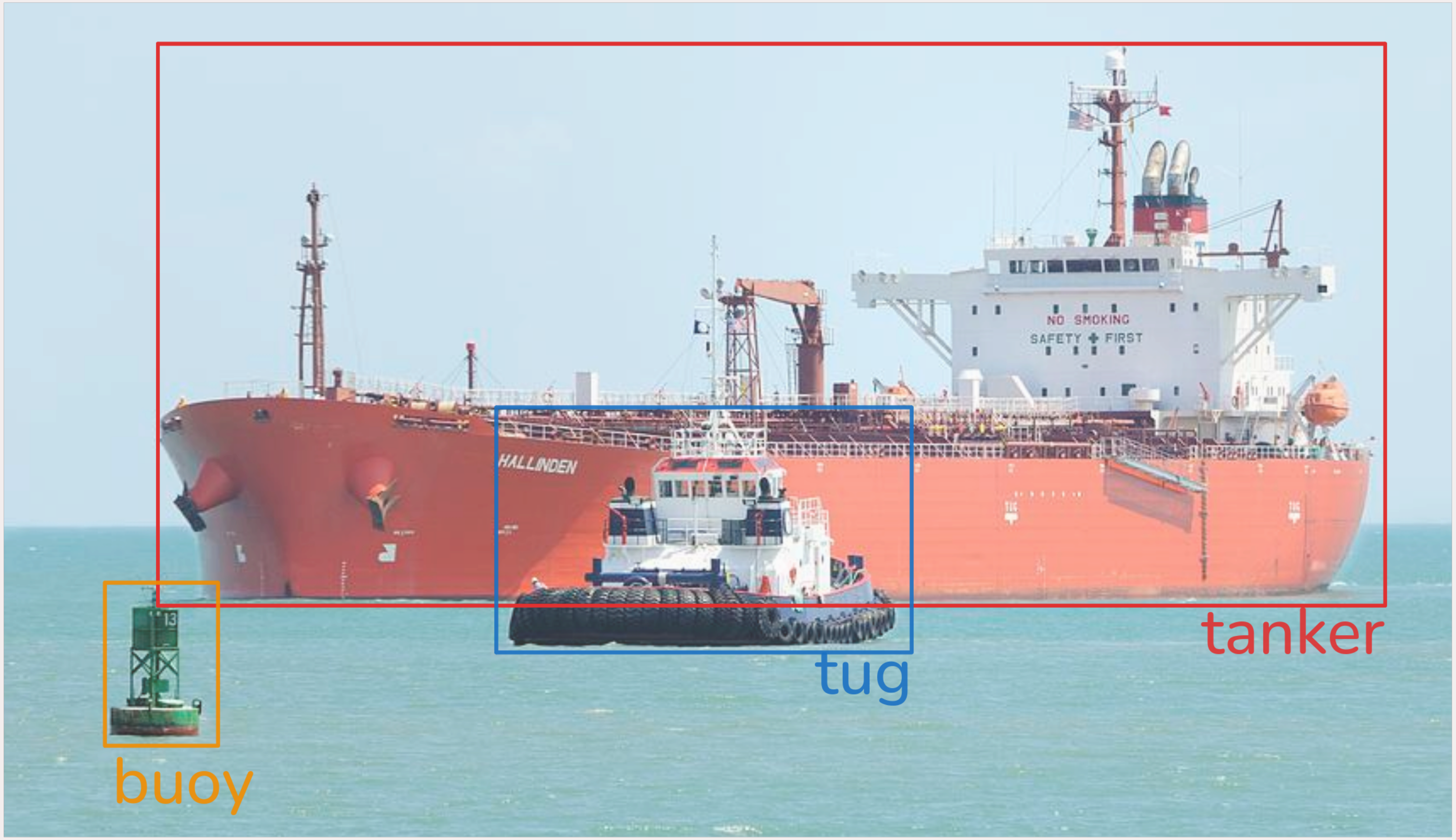
ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

(Karen Simonyan and Andrew Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, International Conference on Learning Representations, 2015)

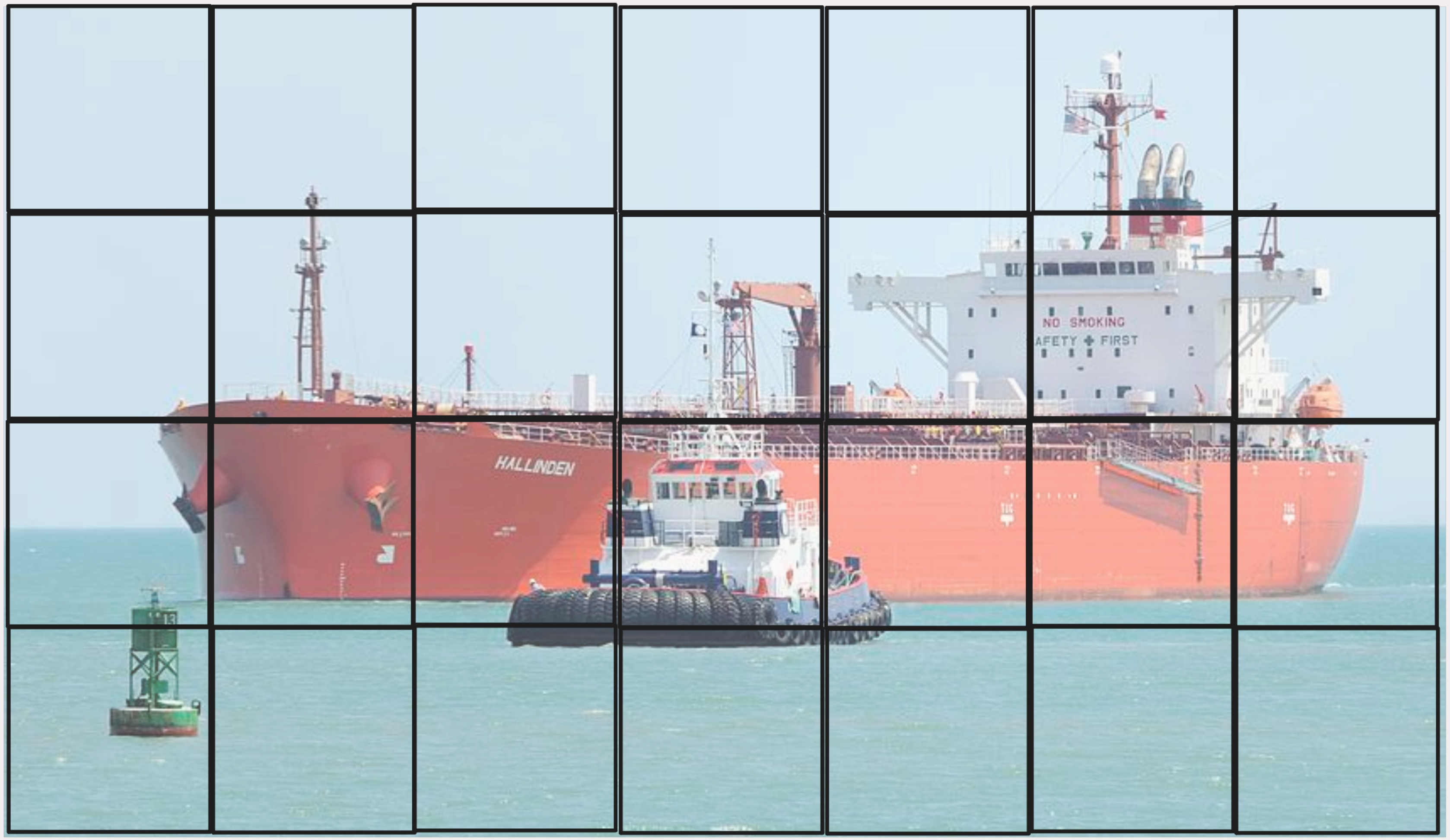
Okay, But What Even Is YOLO



Real-Time Object Detection



Divide Image Into Grid Cells



Grid Cells

Each:

- Predict bounding boxes
  - x, y, w, h, confidence
- Predict probabilities
  - $P(Class|Object)$
  - (for all classes)

Output Tensor

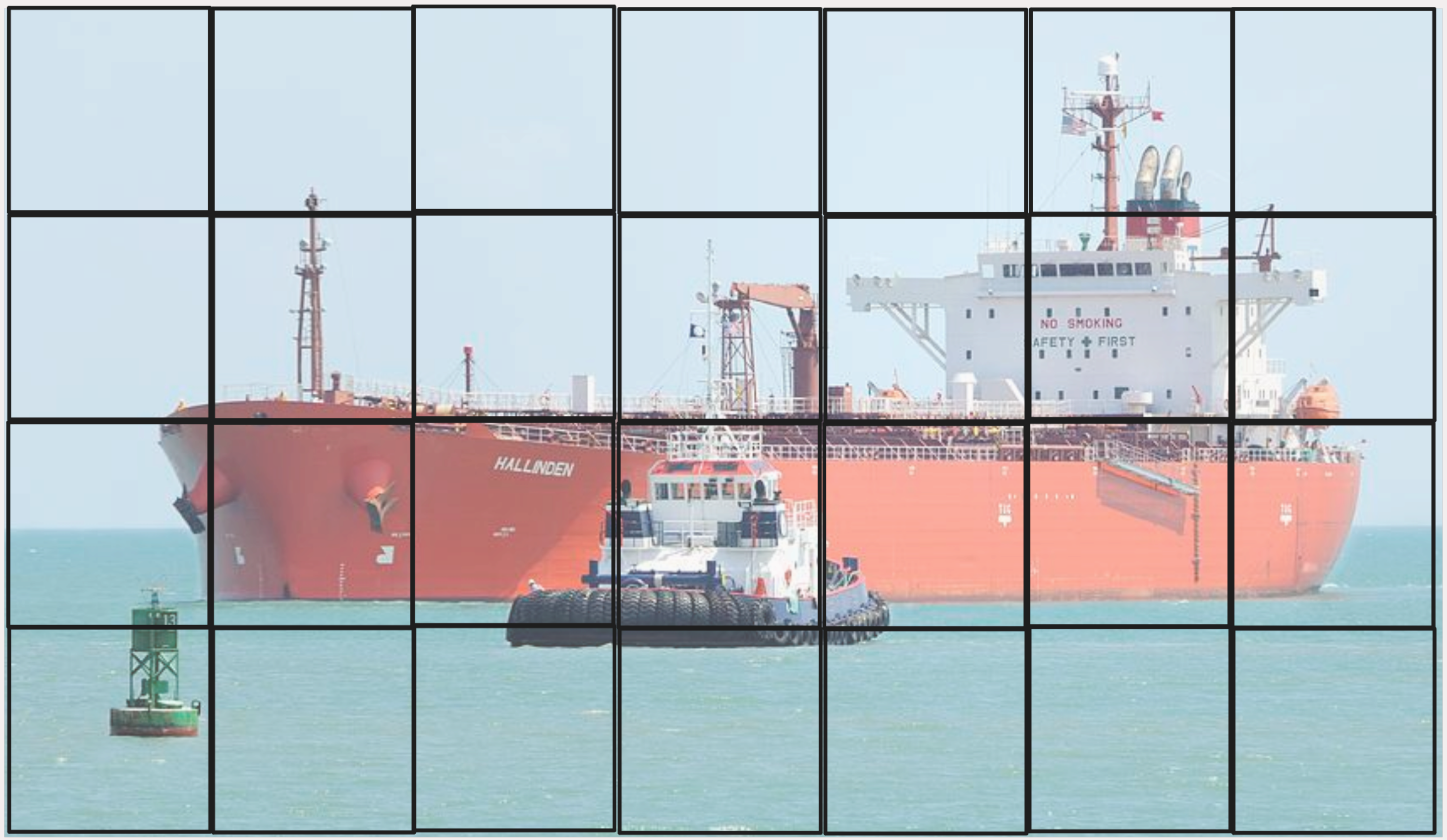
- B bounding boxes
  - x, y, w, h per box
- $S \times S$ grid cells
- C classes

Dimension:

$$(B \times 5 + C) \times S \times S$$

Output Tensor

$$(B \times 5 + C) \times S \times S$$



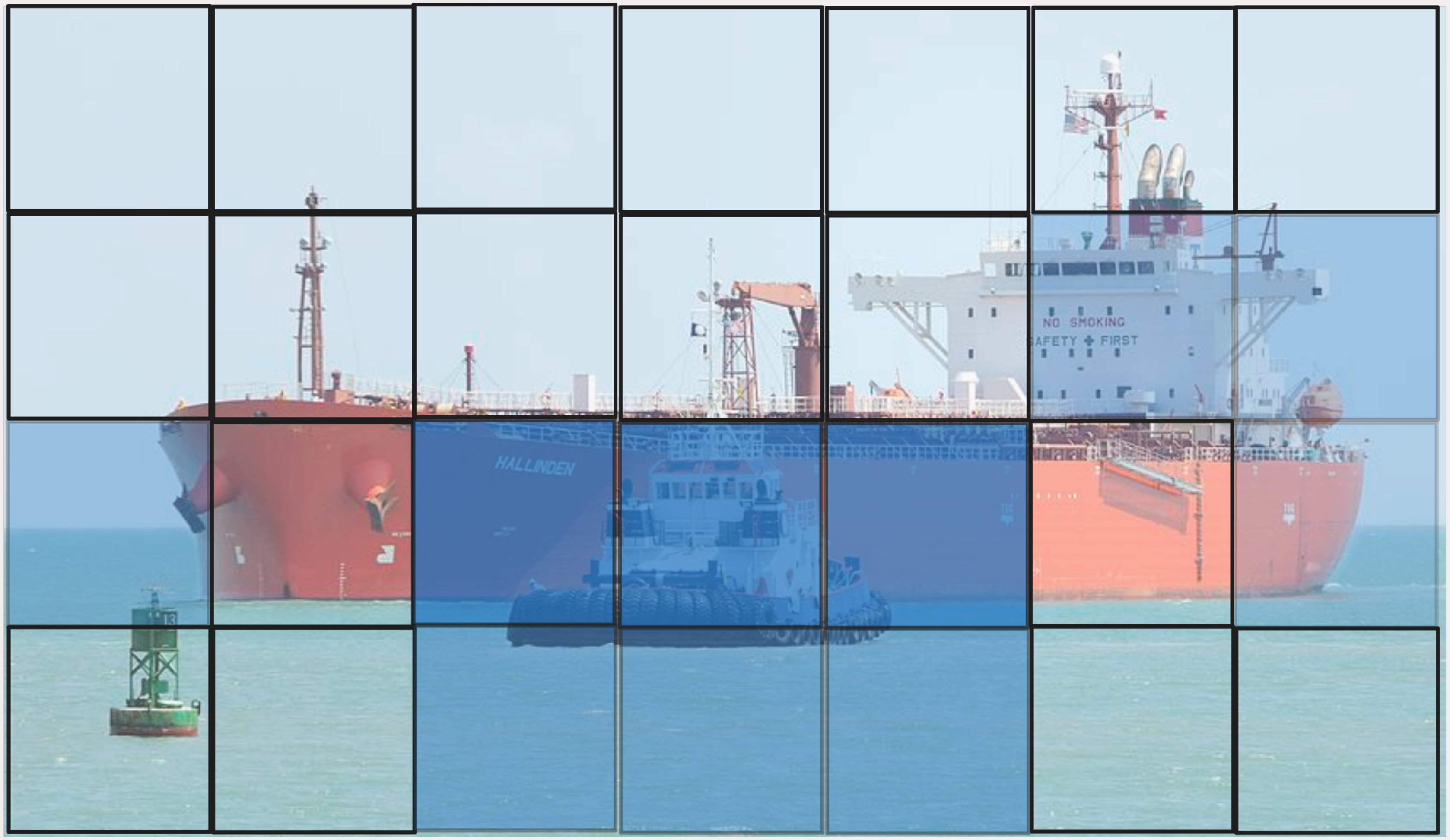
Bounding Boxes

Bounding Boxes

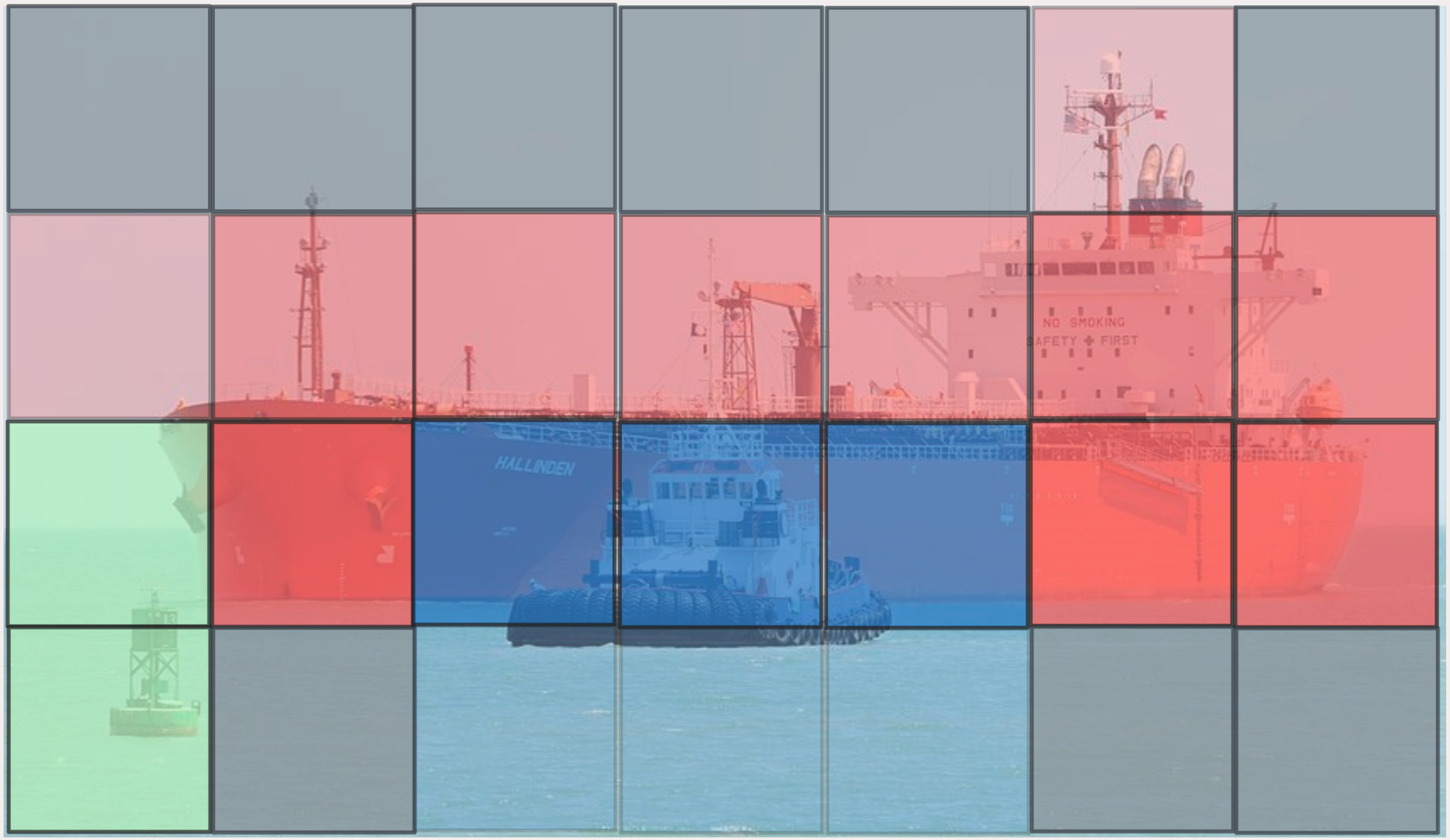
Bounding Boxes

Probabilities

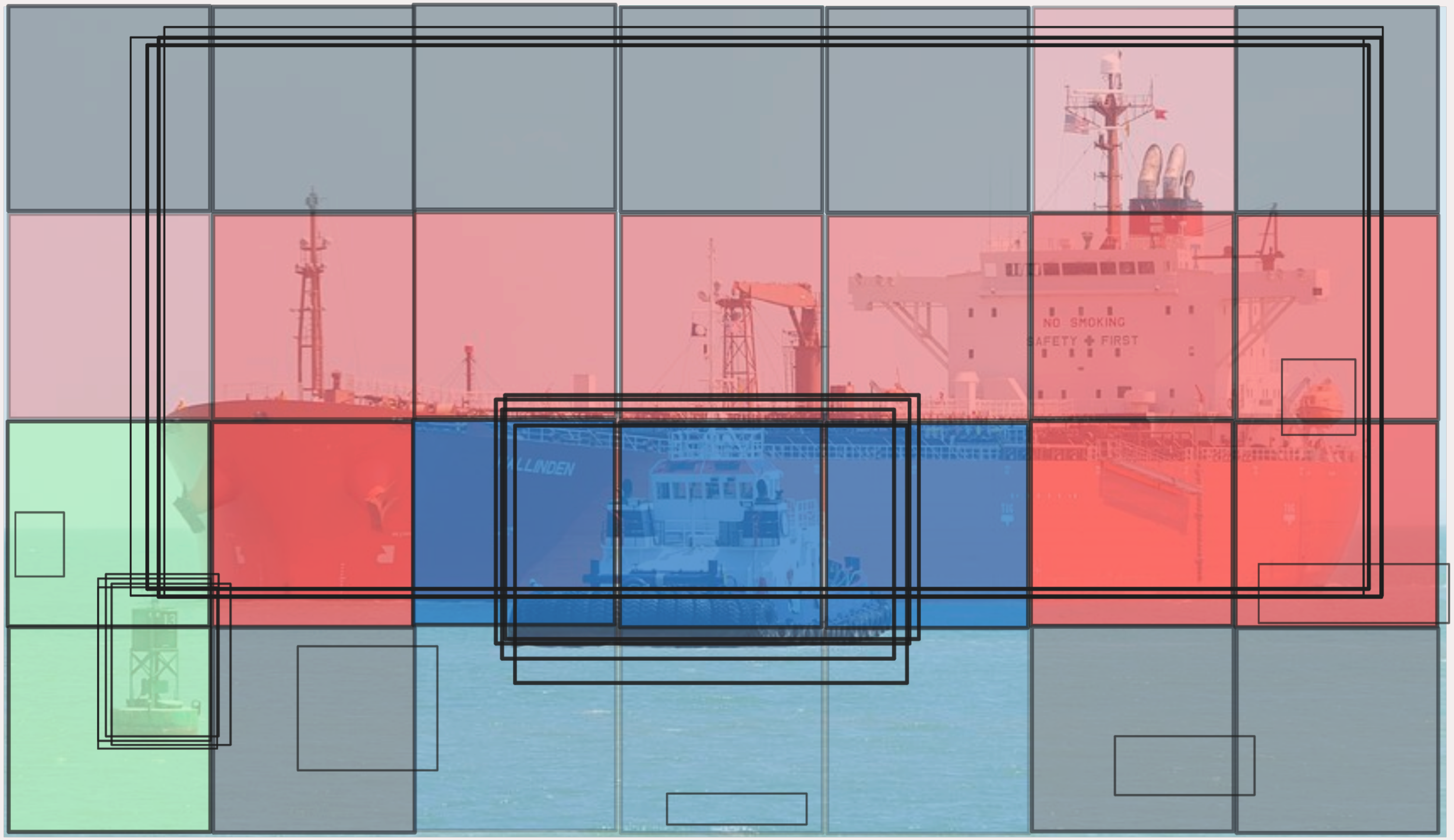
Probabilities



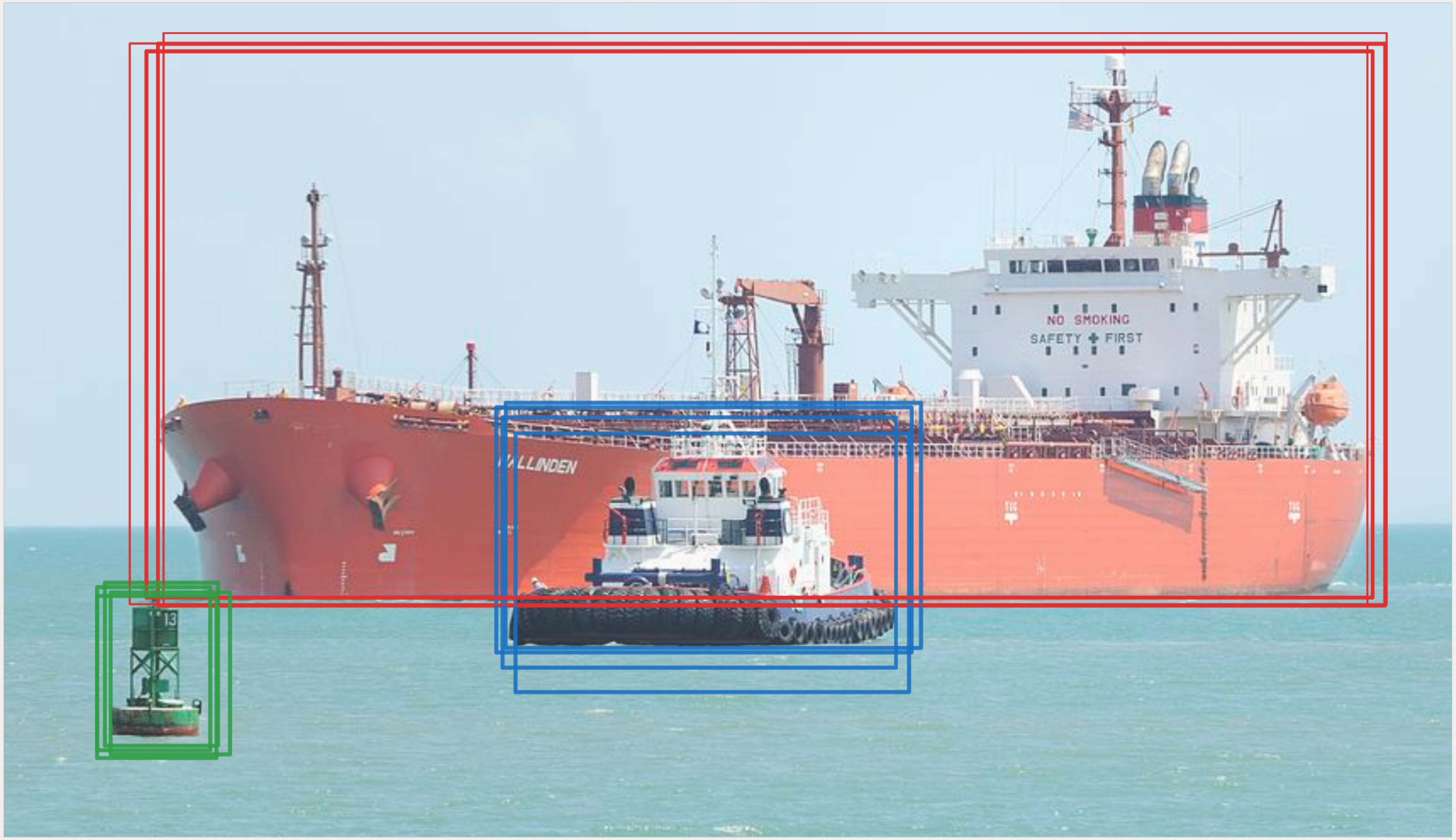
Probabilities



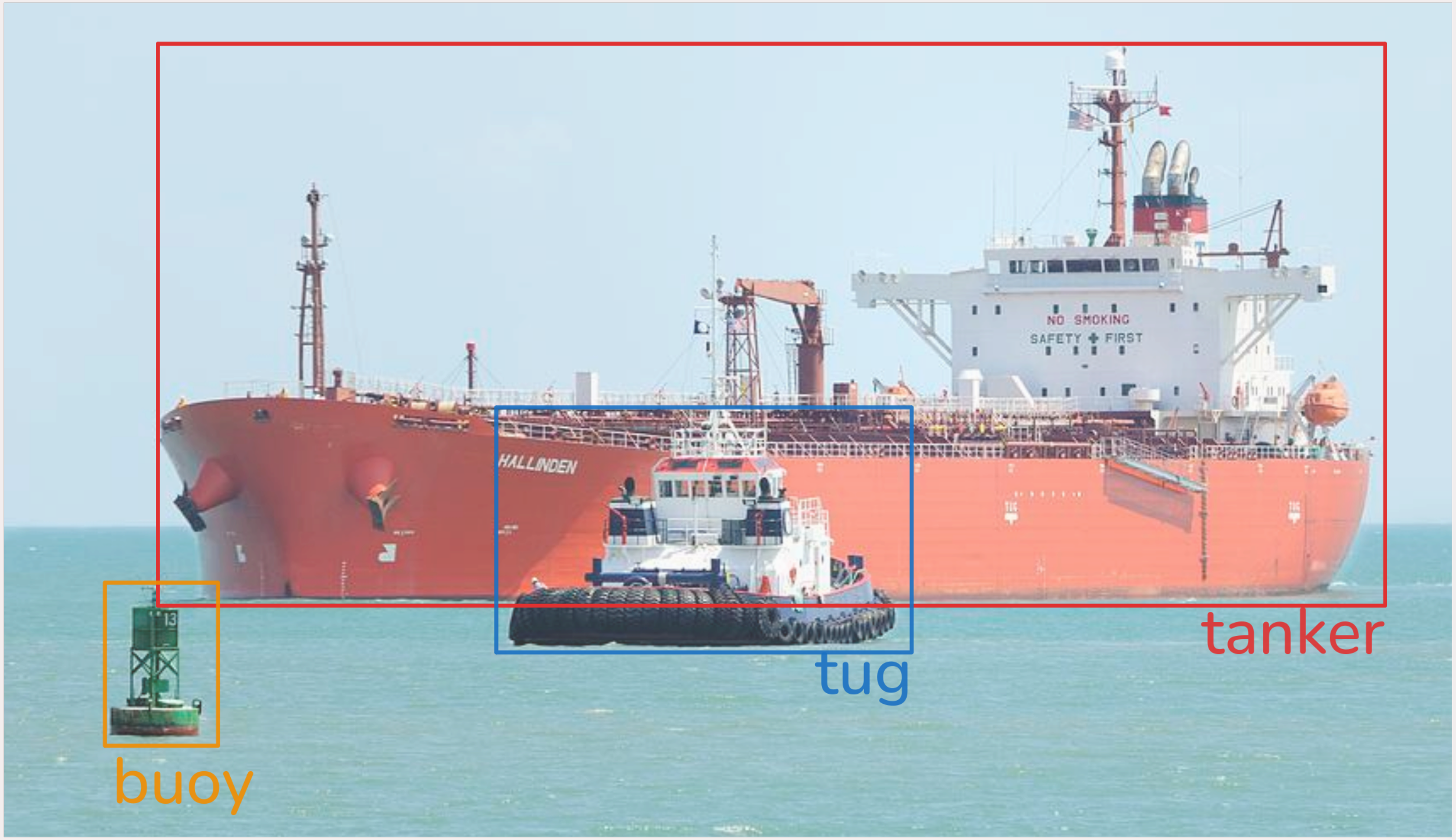
Combining



Non-Maximal Suppression



YOLO 😎



References

- *Deep Learning* by Ian Goodfellow and Yoshua Bengio and Aaron Courville
- *Deep Learning with Python (2nd edition)* by Francois Chollet
- *The Little Book of Deep Learning* by François Fleuret
- You Only Look Once: Unified, Real-Time Object Detection by Joseph Redmon et al.